Variance-based sensitivity analysis of a wind risk model - Model behaviour and lessons for forest modelling

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Highlights:

- The Sobol' method for correlated variables is applied to a complex wind-risk model.
- The results are interpreted from the viewpoints of model users and modellers.
- The variance-based approach is sensitive to the variables correlation structure.
- Rooting depth and soil type provide minor contribution to the outputs variance.
- ForestGALES models the dynamics of wind damage to forest stands very effectively.

Abstract:

We submitted the semi-empirical, process-based wind-risk model ForestGALES to a variance-based sensitivity analysis using the method of Sobol' for correlated variables proposed by Kucherenko et al. (2012). Our results show that ForestGALES is able to simulate very effectively the dynamics of wind damage to forest stands, as the model architecture reflects the significant influence of tree height, stocking density, dbh, and size of an upwind gap, on the calculations of the critical wind speeds of damage. These results highlight the importance of accurate knowledge of the values of these variables when calculating the risk of wind damage with ForestGALES. Conversely, rooting depth and soil type, i.e. the model input variables on which the empirical component of ForestGALES that describes the resistance to overturning is based, contribute only marginally to the variation in the outputs. We show that these two variables can confidently be fixed at a nominal value without significantly affecting the model's predictions. The variance-based method used in this study is equally sensitive to the accurate description of the probability distribution functions of the scrutinised variables, as it is to their correlation structure.

Keywords:

Method of Sobol'; Assessment of model performance; Copula method; Correlated variables

Software availability:

Name of software: ForestGALES Developers: Forest Research, INRA, and the University of Edinburgh. Contact address: Forest Research, Northern Research Station, Roslin, Midlothian EH25 9SY, United Kingdom Email: forestgales.support@forestry.gsi.gov.uk Availability and Online Documentation: The software along with supporting material is freely available. Go to http://www.forestresearch.gov.uk/forestgales to find out how to obtain the software or email forestgales.support@forestry.gsi.gov.uk Year first available: 2000 Hardware required: IBM compatible PC Software required: MS Windows Programming language: Borland Delphi 5.0®. Versions have also been written in Python, Fortran, R and Java. Contact Prof. Barry Gardiner (barry.gardiner@bordeaux.inra.fr) for further details. Contact the corresponding author (tom.locatelli@ed.ac.uk) for information on the R version. Program size: 10 MB. With all additional support files and manuals ¼ 25 MB. For free professional tools for sensitivity analysis please visit the European Commission Joint Research Centre sensitivity analysis page at https://ec.europa.eu/jrc/en/samo/simlab Please contact Dr. Stefano Tarantola (stefano.tarantola@jrc.ec.europa.eu) for information on the Matlab scripts of the Sobol' method for the case of correlated variables.

1. Introduction

Environmental modelling has become a crucial part of the study of environmental phenomena. Significant advances in the fields of hardware and computing now allow for the creation of complex, computationally-demanding, process-based models, aimed at the investigation of natural systems (e.g. Nossent el al., 2011). These complex models are extensively adopted in support of decision-making and for environmental policy settings (e.g. Rahmstorf et al. (2007) on IPCC projections). While a large amount of time and resources are spent to formalise nature in mathematical terms, considerably less effort is often made to investigate the behaviour of mathematical models, which is often done as an "afterthought" (Saltelli and Funtowicz, 2014). As elegantly discussed by Oreskes et al. (1994), the same practices of model validation, evaluation, and confirmation, are philosophical and practical minefields. Modellers are confronted with these issues for a number of reasons: natural systems, which are inherently open in nature, are forced into closed systems to obtain mathematical solutions; scaling issues can arise when the scales at which some elements of a model are calculated differ from the scale of application of the model; nonuniqueness of modelling approaches might result in a faulty model providing "reasonable" outputs (Oreskes et al., 1994). Ultimately, however, the main issue with environmental modelling is the same reason why models are built: we can never exactly know all the data, and those that we do know, we do so with a degree of uncertainty. With regards to the modelling process, in our paper we refer to uncertainty as incomplete knowledge of parameter values (Gaber et al., 2009). Deterministic approaches to modelling require elimination of these uncertainties, thus effectively further removing a model from its intended representation of reality. The inadequacy of the attempts to eliminate at all costs the uncertainties of the parameters and variables of a model, in order to produce completely deterministic results, is nowadays generally accepted (e.g. Penman et al., 2003). The transparency of model predictions is an important requirement especially when models are applied for decision-making, and in policy frameworks (e.g. the US Environmental Protection Agency, see Gaber et al. (2009)). To this end, uncertainty analysis is normally applied to quantify the uncertainties of the input variables, parameters, and outputs of a model, thus providing some insight on the reliability and the applicability range of the model.

On the other hand, the issue of sensitivity of model predictions to variation in model parameters and variables is still relatively underestimated. Quoting Saltelli et al. (2004), a sensitivity analysis is *"The study of how uncertainty in the output of a model (…) can be apportioned to different sources of uncertainty in the model input*". However, when performed appropriately (Saltelli and Annoni, 2010), sensitivity analysis (SA) of mathematical models is a tool that can help with fundamental issues about the robustness and the behaviour of a model (Tarantola et al., 2002; Norton, 2015). A number of techniques exist to perform sensitivity analysis (see https://ec.europa.eu/jrc/en/samo/methods). These can be broadly divided in two groups, typically referred to as "local" and "global", on the basis of the region of the input space that is scrutinised in the analysis. Local SA are normally based on derivatives of the output Y with respect to one factor X_i (e.g. $\delta Y / \delta X_i$), where by factor here we denote either a model parameter or an input variable. These derivatives are often normalised by the input-output standard deviations (they are said to be sigma-normalised) to produce more robust sensitivity indices, as recommended by the Intergovernmental Panel on Climate Change in their guidelines on the inventories of greenhouse gases (IPCC, 1999; IPCC, 2000). However, with this approach only the base point where the derivatives are computed is investigated, which is an issue

when the model is of unknown linearity (Saltelli et al., 2008). Local derivatives-based methods are mostly adopted within the context of one-at-a-time (OAT) approaches, where only one factor is perturbed while all the others are fixed at a nominal value (usually the mean). Therefore, the effects of factors interactions on the output variance are neglected with OAT methods, which are therefore only applicable for strictly additive models (Campolongo and Saltelli, 1997). Global SA (GSA) methods, on the other hand, allow for the exploration of the entire range of the factors, and for simultaneous perturbation of all the factors. The most powerful GSA methods are variance-based techniques that decompose the total variance of the output into conditional variances for single factors and for sets of factors. These techniques include the importance measures of Iman and Hora (1990) and of Sacks et al. (1989), the FAST (Fourier Amplitude Sensitivity Test) method (Cukier et al., 1973; Cukier et al., 1978) and the extended FAST (Saltelli et al., 1999), and the method of Sobol' (Sobol', 2001). The last two approaches can be solved numerically with Monte Carlo methods. Derivatives-based methods have been developed for global sensitivity measures (DGSM, e.g. Kucherenko et al., 2009; Sobol' and Kucherenko, 2009). The values of DGSM is exactly equal to that of total sensitivity indices calculated with the Sobol' method (see section 2.2.1) in a number of cases, e.g. for linear models, while in a general case they correspond to the upper bound of the total Sobol' indices, with the advantage of a much shorter computational time. Variance-based GSA methods have a number of advantages: they are model-independent; they can capture the influence of the full range of variation of each input variable; they allow for the investigation of interaction effects amongst variables; and they provide the possibility of grouping factors (Saltelli et al., 2008). Their drawback is the high computational cost required for performing such techniques, due to the large number of model executions required for the convergence of the values of the sensitivity indices (Kucherenko et al., 2012). For this reason, a large body of research has been devoted to devise efficient algorithms for their computation (e.g. Kucherenko et al., 2012; Mara and Tarantola, 2012; Most, 2012; Saltelli, 2002).

Of the aforementioned variance-based GSA techniques, the method of Sobol' has found favour with modellers in the environmental sciences, because of the relatively straightforward interpretation of the sensitivity indices calculated with this method, and because it very efficiently samples the factors space (Sobol', 1990; Yang, 2011; Kucherenko et al., 2015). The Sobol' method is often used as a benchmark against which to compare the results of other SA techniques (Confalonieri et al., 2010). In a previous issue of this journal, Nossent et al. (2011) successfully applied the Sobol' method to the identification of the most, and the least, important factors in a SWAT model (Soil and Water Assessment Tool). The authors also provided an exhaustive description of the Monte Carlo procedures required for the calculation of the Sobol' sensitivity indices. Song et al. (2012) used the method of Sobol' for the SA of the 3-PG2 forest growth model, aimed at model calibration. A known issue with variance-based GSA techniques is how to account for correlation between factors when calculating the conditional variances. Indeed, correlation amongst factors in environmental models is typical. A number of studies propose methods to obviate the issue of dependent factors in GSA (e.g. Mara and Tarantola, 2012; Most, 2012).

In this paper, we submit ForestGALES, a forest wind-risk model, to a variance-based GSA using the method of Kucherenko et al. (2012), a generalisation of the method of Sobol' for correlated factors. The rationale of ForestGALES, together with the most important model calculations for the context of our GSA, is discussed in the Methods section. For a thorough description of the model, the interested reader is referred to Hale et al. (2015), published in a previous issue of this journal.

Variance-based GSA are normally applied to complex models composed of a large number of factors, sometimes in excess of one hundred, mostly for the direct benefit of the modelling community. In this paper, we limit our GSA to the inputs of ForestGALES that are controllable by the end-users. Focussing on those input variables that are user-modifiable extends the benefits of a GSA to the end-user base of an environmental model, and facilitates the interpretation of the results of the SA in a practical setting. To extend the results of our GSA to a large user-base community, we perform our GSA on three species *(Picea sitchensis* (Bong.) Carr., *Pinus pinaster* (Ait.), and *Eucalyptus globulus* (Labill.)), representative of three of the most extensively planted and highly productive tree genera worldwide: spruces, pines, and eucalypts. We also investigate the differences in the ranking of the influential variables between the three species, to evaluate whether the sensitivity of the model to its input parameters is the same across the species used in the simulations. In this paper we focus our attention on two questions that SA can help with: (1) What model inputs should a user of ForestGALES focus on knowing more accurately to maximally reduce the uncertainty in the model predictions? (2) What model inputs contribute the least to the variation in the output? The first question can be answered under the Factor Prioritisation setting of GSA, while the second pertains to the Factor Fixing setting (Saltelli et al., 2008), discussed in the Methods section.

2. Materials and methods

2.1 The ForestGALES model

ForestGALES is a semi-mechanistic, process-based model that uses tree and stand characteristics for the calculation of the critical wind speeds (CWS) that result in tree uprooting and stem breakage, and combines them with information on the local wind climate to estimate the associated risks of wind damage to forest stands (Hale et al., 2015). The model is based on engineering principles (Gardiner et al., 2008) and requires only a small number of user inputs. These include: tree species, which is used as a trigger to call species-specific sub-modules; tree-level variables, such as dominant tree height (i.e. the average height of the hundred largest trees per hectare) and diameter at breast height (*dbh*, measured at 1.3m height on the stem); and stand-level variables, such as stocking density (*Sph*, stems per hectare), soil type, rooting depth, and size of any upwind gaps. Estimation of the risk of damage requires a characterisation of the local wind climate. In Britain, where the model was initially developed, this is done with DAMS scores (Detailed Aspect Method of Scoring), which relate topographic characteristics of a site to the rate of tatter of tatter flags to estimate the windiness of the site (Quine and White, 1993). For instance, a DAMS score of 10 represents very sheltered conditions, a score of 17 is considered as quite exposed (Mason, 2003), and a score of 20 often corresponds to the limit for commercial forestry (Quine, 2000). DAMS scores are converted internally to the model to scale and shape parameters of a Weibull distribution. Weibull distributions have been recently reviewed as the most reliable and effective methods for describing distributions of wind speed and directions (Seguro and Lambert, 2000). Because of the extreme sensitivity of the Weibull distribution, small changes in CWS can result in large differences in the probability of extreme events (Gardiner et al., 2008). The rationale of ForestGALES and the interplay between the inputs are shown in Figure 1.

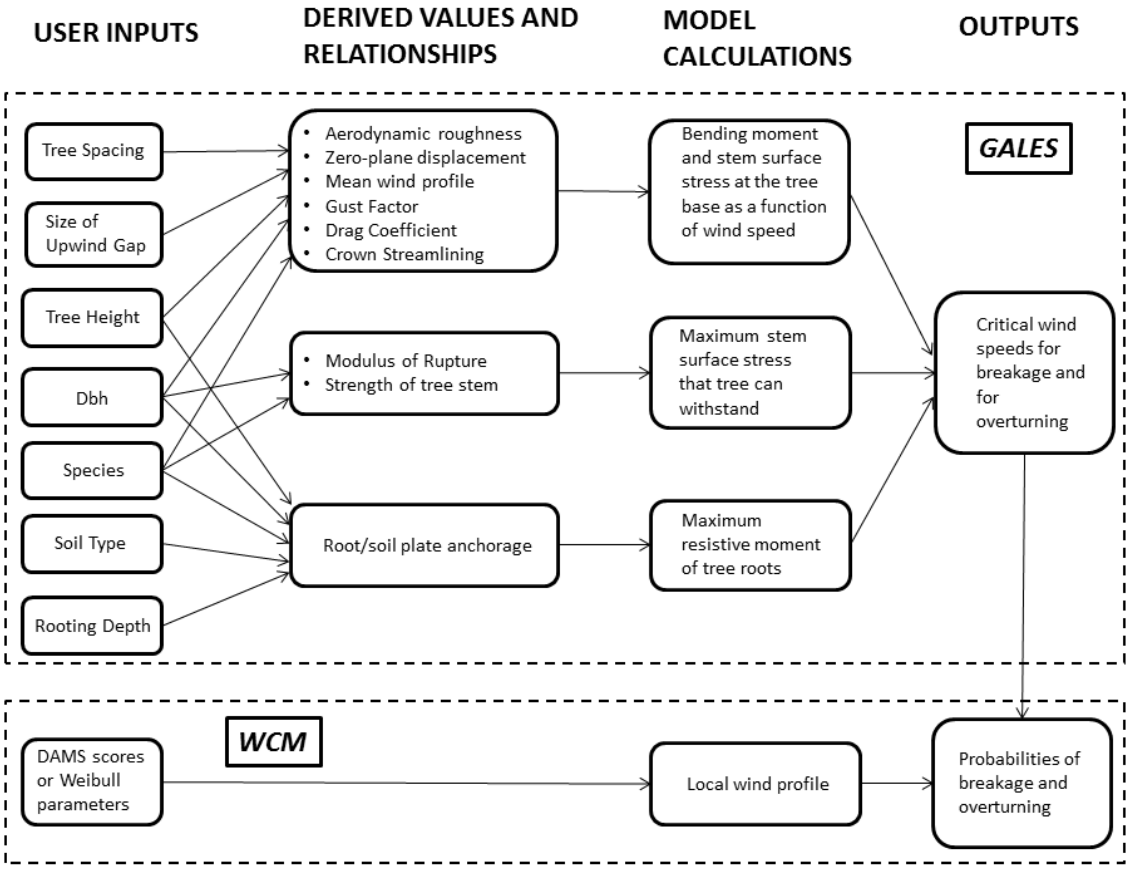


Figure 1: Basic schematic representation of the rationale of ForestGALES from the point of view of user-defined input variables (adapted from Gardiner et al., 2000). The dashed boxes delimit the two main modules. GALES calculates the critical wind speeds for breakage and overturning. WCM: Wind Climate Module, where the probabilities of breakage and overturning are calculated.

The diagram in Figure 1 shows that ForestGALES is composed of two main modules: the first one, often referred to simply as GALES (Gardiner et al., 2000), makes use of tree and stand variables to calculate the CWS for breakage and overturning (henceforth: $CWS_{(B, O)}$). In GALES, tree height and *dbh* are featured in the calculations of canopy dimensions and aerodynamic properties, as well as being involved in the calculations of the mean wind profile, together with *Sph* and size of an upwind gap. Soil type and rooting depth are used in species-specific sub-modules to retrieve the values of species-specific coefficients (C_{reg}) of linear regressions of total overturning moment, as measured empirically in the field, against stem weight under different soil types and rooting depths. These relationships are derived from tree-pulling fieldwork data used in species parameterisations of ForestGALES (see Nicoll et al. (2006) for *P. sitchensis*; Cucchi et al. (2005) for *P. pinaster*; and Locatelli et al. (2016) for *E. globulus*). For *E. globulus*, only one value is available because tree-pulling was

performed only in one location with homogeneous soil type (162.32 N m kg^{-1}, from Locatelli et al., 2016). The values of C_{reg} for *P. sitchensis* and *P. pinaster* are shown in Table 1.

Table 1: Values of the linear regressions of total overturning moment vs stem weight, for combinations of rooting depth (shallow, medium, and deep) and soil type (freely draining, gleys, mineral peats, and deep peats). *P. sitchensis* and *P. pinaster* are shown here. Only one value available for *E. globulus* (162.3, from Locatelli et al., 2016). Units are N m kg^{-1}. s.d. denotes the standard deviation.

Picea sitchensis		Rooting depth				
		Shallow	**Medium**	**Deep**	**Soil Average**	**Soil s.d.**
Soil Type	**Freely draining**	153.2	156.2	178.1	162.5	13.6
	Gleys	135.4	138.5	157.9	143.9	12.2
	Mineral peats	147.8	151.2	172.5	157.2	13.4
	Deep peats	168.1	172.1	196.2	178.8	15.2
	Depth average	*151.1*	*154.5*	*176.2*		
	Depth s.d.	*13.5*	*13.9*	*15.8*		

Pinus pinaster		Rooting depth				
		Shallow	**Medium**	**Deep**	**Soil Average**	**Soil s.d.**
Soil Type	**Freely draining**	125.8	168.8	144.5	146.4	21.6
	Gleys*	124.2	144.4	126.7	131.8	11.0
	Mineral peats*	135.6	157.7	138.3	143.9	12.1
	Deep peats*	154.3	179.4	157.3	163.7	13.7
	Depth average	*135.0*	*162.6*	*141.7*		
	Depth s.d.	*13.8*	*15.0*	*12.8*		

*C_{reg} values of soil types: gleys, mineral peats, deep peats for *P. pinaster* are taken from those of *P .sylvestris* (L.)

Soil type and rooting depth do not contribute to the calculation of CWS_B, and therefore for this output they are expected not to be flagged as important in the SA. Hale et al. (2015) exhaustively describe the structure of ForestGALES. In this paper we limit ourselves to showing the final formulas for the calculations of $CWS_{(B,\,O)}$, for the discussion of the results of the SA

$$\boldsymbol{CWS_B} = \frac{1}{kD}\left[\frac{\pi * MOR * dbh^3}{32\rho G(d-1.3)}\right]^{\frac{1}{2}}\left[\frac{f_{knot}}{f_{CW}}\right]^{\frac{1}{2}}\ln\left(\frac{h-d}{z_0}\right) \quad (1)$$

$$\boldsymbol{CWS_O} = \frac{1}{kD}\left[\frac{C_{reg} * SW}{\rho G d}\right]^{\frac{1}{2}}\left[\frac{1}{f_{CW}}\right]^{\frac{1}{2}}\ln\left(\frac{h-d}{z_0}\right) \quad (2)$$

Where k is von Karman's constant (0.4, dimensionless); D (m) is the mean tree spacing, calculated as $1/\sqrt{sph}$; MOR is the Modulus of Rupture (Pa) of green wood; ρ is the air density (kg m^{-3}); G is a "gust factor" (dimensionless), used to convert the calculated mean bending moments to maximum bending moments; d is the zero-plane displacement (m), i.e. the height up the tree at which the wind can be regarded as acting on a single point (Raupach, 1994); f_{knot} (dimensionless) is a factor to account for the presence of wood knots, the values of which vary with species and typically range between 0.8 and 1 (Ruel et al., 2010), and can decrease wood strength (Lavers, 1969); f_{CW} is a tree mass factor (dimensionless), which accounts for the additional turning moment provided by the tree canopy as a tree sways from its vertical axis under the action of the wind; h is the average tree height (m); z_0 is the canopy roughness (m); C_{reg} (dimensionless) is described above; and SW is stem weight (kg). Table 2 shows the input variables involved in the calculations of the non-constant terms in Eq. (1) and (2).

Table 2: Mapping between ForestGALES input variables and the non-constant terms of the formulas for the calculations of the critical wind speeds for breakage (CWS_B) and overturning (CWS_O). Species is used as a trigger to select species-specific sub-modules; [a]Rooting depth and Soil type are involved in the calculations of d, f_{CW}, and z_0 only for CWS_O; [b]C_{reg} values are empirically derived (see main text for a brief explanation, or Nicoll et al. (2006) for a complete description of tree-pulling fieldwork techniques). The symbol (✓) denotes which formula variables are present in the corresponding calculations of the critical wind speeds for breakage and overturning.

Formulas Variables		CWS_B	CWS_O	Input Variables
D	Mean tree spacing	✓	✓	Sph
G	Gust Factor	✓	✓	Tree height; Sph; Gap Size
d	Zero-plane displacement	✓	✓	Tree height; Dbh; Sph; Gap Size; Rooting depth[a]; Soil type[a]
f_{CW}	Tree mass factor	✓	✓	Tree height; Dbh; Sph; Gap Size; Rooting depth[a]; Soil type[a]
h	Mean tree height	✓	✓	Tree height
z_0	Canopy roughness	✓	✓	Tree height; Dbh; Sph; Gap Size; Rooting depth[a]; Soil type[a]
C_{reg}[b]	Overturning moment multiplier		✓	Rooting depth; Soil type
SW	Stem weight		✓	Tree height; Dbh

In the second main module of ForestGALES (see Figure 1), the local wind climate is used to calculate the return period of a storm with maximum mean wind speeds that would match, or exceed, the calculated $CWS_{(B, O)}$. The probabilities of breakage and overturning (henceforth: $Prob_{(B, O)}$) are calculated as the inverse of the return period. We refer to the second main module as "wind climate module" (WCM).

2.2 Procedure for the GSA of ForestGALES

The variance-based GSA method for correlated variables described in Kucherenko et al. (2012) is a generalisation of the traditional Sobol' method for the calculation of the first-order and total sensitivity indices (Sobol', 2001). First-order indices convey information on the direct contribution of an input to the output's variance, and are therefore sometimes referred to as "importance

measures" (e.g. in Homma and Saltelli, 1996). Total indices account for the total contribution of an input to the output's variance, by including all interaction effects with other variables (Saltelli, 2002). Nossent et al. (2011) provide a thorough and accessible explanation of the theory and the mathematics adopted in the method of Sobol'. Here, we limit ourselves to providing a general description of this approach, before briefly discussing the modifications contributed by Kucherenko et al. (2012) for the case of correlated inputs.

2.2.1 The original method of Sobol'

The original method of Sobol' is based on the propagation of the uncertainties in the inputs to the outputs. The uncertainty in the inputs is expressed via independent marginal distribution functions. This method is similar to ANOVA techniques, in that the model output variance V is decomposed into summands (partial variances) of increasing dimensionality. These partial variances are calculated for each X_i, (representing the importance of main effects) for pairs X_i and X_j, (representing the importance of interactions between pairs) and finally for groups of inputs, such as $X_i,X_j,...X_m$, (representing the importance of higher order interactions)(Sobol', 2001). First order sensitivity indices of the output Y to the inputs X_i can then be introduced, simply by normalizing the first order variances V_i by the total variance V (Sobol', 2001). This is commonly done using the variance of the expectation of Y conditional on a fixed value of X_i, by averaging for all values of X_i (Saltelli et al., 1999), as shown in Eq. (3).

$$\boldsymbol{S_i = \frac{V(E(Y|X_i)}{V_Y}} \quad \textbf{(3)}$$

Where the S_i is the first order sensitivity index for X_i, the numerator is the conditional variance, and V_Y is the total variance of Y. With the method of Sobol', total sensitivity indices (S^T_i) can be computed by grouping together all the variables but the one for which the S^T_i are calculated. Total indices can be calculated with Eq. (4).

$$\boldsymbol{S_i^T = 1 - V_{X_{-i}}/V_Y} \quad \textbf{(4)}$$

where $V_{X_{-i}}$ is the variance of all the variables except X_i, for which the indices are calculated. By repeating for all X_i, it is possible to calculate the total effects of all the input variables. First order and total sensitivity indices are computed with Monte Carlo techniques, at the cost of $N(m + 2)$ model runs, where N is the sample size and m the number of model inputs (Archer et al., 1997; Chan et al., 1997).

2.2.2 Generalisation of the Sobol' method for the case of correlated variables

In the case of correlated inputs, describing the inputs uncertainty solely with independent marginal distribution functions is inadequate. Kucherenko et al. (2012) suggest sampling from both the joint and conditional distribution functions of the inputs, which requires providing the correlation matrix

of the inputs. When at least one of the inputs is non-normally distributed, the authors suggest the use of a Gaussian copula to generate the correlated sample. This technique is widely used in studies of financial risk (e.g. Cherubini et al., 2004). In this setting, correlated inputs are described by their marginal distribution and a measure of their correlation with the other inputs:

$$\boldsymbol{C}(\boldsymbol{G_1}(\boldsymbol{X_1}), \dots, \boldsymbol{G_n}(\boldsymbol{X_n});\ \boldsymbol{\Sigma_X}) = \boldsymbol{F_n}\left(\boldsymbol{F^{-1}}\left(\boldsymbol{G_1}(\boldsymbol{X_1})\right), \dots, \boldsymbol{F^{-1}}\left(\boldsymbol{G_n}(\boldsymbol{X_n})\right);\ \boldsymbol{\Sigma}\right) \quad \textbf{(5)}$$

Where *C* denotes the copula; $G_{1\dots n}$ are the marginal univariate cumulative distribution functions; $X_{1\dots n}$ are the original inputs; Σ_X is the original correlation matrix; F_n is the multivariate cumulative *normal* distribution function; F^{-1} is the inverse normal cumulative distribution function; and Σ is the correlation matrix of the corresponding joint *normal* distribution function. With this approach, the original correlation matrix Σ_X of an original input vector $\boldsymbol{X}$ is mapped to the correlation matrix Σ. The adoption of copulas is convenient for SA because all the information on the dependencies between inputs is contained in the copula, while the information contained in the marginal distributions of the inputs is provided by the marginal univariate *cumulative* distribution functions of the inputs (Sklar, 1973). In our study we used eq. 5.4 and 5.6 in Kucherenko et al. (2012) for the calculations of S_i and S^T_i, respectively, at a cost of $N(2m + 2)$ (35,200 in our case) model runs, using the Quasi-Monte Carlo method of Sobol' applied to the case of correlated variables (Sobol', 1990; Kucherenko et al., 2012). Quasi-Monte Carlo methods are commonly used in GSA because they provide enhanced convergence properties in comparison to traditional Monte Carlo methods, and hence require considerably less model executions to achieve a given precision in the estimates (Sobol', 1998; Kucherenko et al., 2012).

2.2.4 Data used in the GSA of ForestGALES

Both the original method of Sobol' and that of Kucherenko et al. (2012) require knowledge of the probability distribution functions of the inputs for the generation of the samples. Describing the inputs with appropriate PDFs is a requirement of GSA methods, in order to ensure that the pseudo-random numbers generated with Monte Carlo methods are representative of the variables distributions. We described some variables (*Sph*, Rooting depth, Soil type, Gap size, and DAMS) with uniform or discrete uniform distributions, using the same distribution parameters for all the species, because we wanted to explore as large an input space as possible with regards to these variables. The gap used in this version of ForestGALES is what is normally referred to as "green edge gap"; that is, a gap that has been in place for some time, rather than a newly exposed one. For tree height and dbh, we found that our data source was well represented with Gaussian distributions. We have therefore fitted normal distributions to tree-pulling data for the three species used in this paper: for *P. sitchensis*, we used data from the UK Forestry Commission tree-pulling database (see Nicoll et al., 2006); for *P. pinaster*, we combined tree-pulling data from Cucchi et al. (2005) with data from a similar species (Scots pine, *Pinus sylvestris* (L.)), from the UK database, because complete data for *P. pinaster* was not available. In fact, tree-characteristics such as canopy structure and the architecture of the rooting system are very similar between *P. pinaster* and *P. sylvestris*. For *E. globulus*, we used tree-pulling data used in Locatelli et al. (2016) for the parameterisation of ForestGALES for this species. The lack of variability in Soil type and Rooting depth for the parameterisation of this particular species means that our study cannot evaluate the sensitivity of ForestGALES to these two variables, and of their contributions to the interactions with each other and the other input

variables, for *E. globulus*. We imposed lower bounds to the distributions of tree height (4m) and dbh (3cm), to ensure that the functional limits of ForestGALES were not exceeded. The parameters of the inputs distributions are shown in Table 3. Our proposed approach is data-driven, i.e. it is an exploration of the behaviour and sensitivity of the ForestGALES model from the point of view of the data used for its parameterisations. This ensures that the operational limits of the model are respected as much as possible, while allowing for large amount of data within the probability density functions of the inputs to explore the input space as thoroughly as possible.

Table 3: Parameters of the probability distribution functions used for the generation of quasi-random samples used for the calculation of sensitivity indices. Parameters calculated from tree-pulling data. Dbh: diameter at breast height (1.3m); Sph: stems per hectare; DAMS: Detailed aspect method of scoring, a measure of the windiness of a site. [a]Lower bound for tree height: 4m. [b]Lower bound for dbh: 3cm.

Variable	**Species**	**Parameters of the Normal Distribution**	
		Mean	**sd**
Tree height[a] (m)	*Picea sitchensis*	13.64	2.64
Dbh[b] (cm)		19.89	4.52
Tree height[a] (m)	*Pinus pinaster*	13.70	2.75
Dbh[b] (cm)		18.98	3.51
Tree height[a] (m)	*Eucalyptus globulus*	23.17	4.59
Dbh[b] (cm)		21.78	7.51
	Type of distribution	**Min**	**Max**
Sph	Discrete Uniform	300	3300
Rooting depth	Discrete Uniform	1	3
Soil type	Discrete Uniform	1	4
Gap size (m)	Uniform	0	1000
DAMS	Discrete Uniform	7	22

Based on the data available, we calculated the correlation matrix (Σ_X) of the input variables for the three species for the Gaussian copula required for the GSA, shown in Table 4. As expected, for all the species the most relevant correlation was between tree height and *dbh* (*P. sitchensis*: 0.54; *P. pinaster*: 0.72; *E. globulus*: 0.91. All *p*-values < 0.001). We calculated the correlation between these two variables from species-specific tree-pulling data. Due to the fact that correlation data involving the other variables were only available for *P. sitchensis*, we have applied this to all the species. Gap size and DAMS are not correlated to any other variable. The large values of the Pearson correlation coefficients between tree height and dbh justify the use of the GSA method for correlated variables.

Table 4: Correlation matrices for the ForestGALES input variables for *P. sitchensis*. Dbh: diameter at breast height; Sph: stems per hectare; Gap size and DAMS are not shown because uncorrelated to the other variables. Correlations involving the variables: Sph, Rooting depth, and Soil type, are calculated from *P. sitchensis* data from the UK Forestry Commission's tree-pulling database, and applied to the other two species. [a] The significance of the correlation between pairs of variables with Pearson's correlation coefficient > 0.3 (thus retained in the calculation of the copula) is large (all *p*-values < 0.001)

Picea sitchensis	**Height**	**Dbh**	**Sph**	**Rooting depth**	**Soil type**
Height	**1**	0.54[a]	-0.07	0.22	-0.07
Dbh		**1**	0.04	0.13	-0.02
Sph			**1**	0	-0.28
Rooting depth				**1**	-0.35[a]
Soil type					**1**

In Figure 2 we show the effect of the correlation between Rooting depth and Soil type (Pearson correlation coefficient: -0.35; *p*-value < 0.001) on the sampling matrix calculated with the copula method. The occurrence of the different Soil types modelled in Figure 2 is representative of the *P. sitchensis* tree-pulling database used for the calculation of the correlation coefficients.

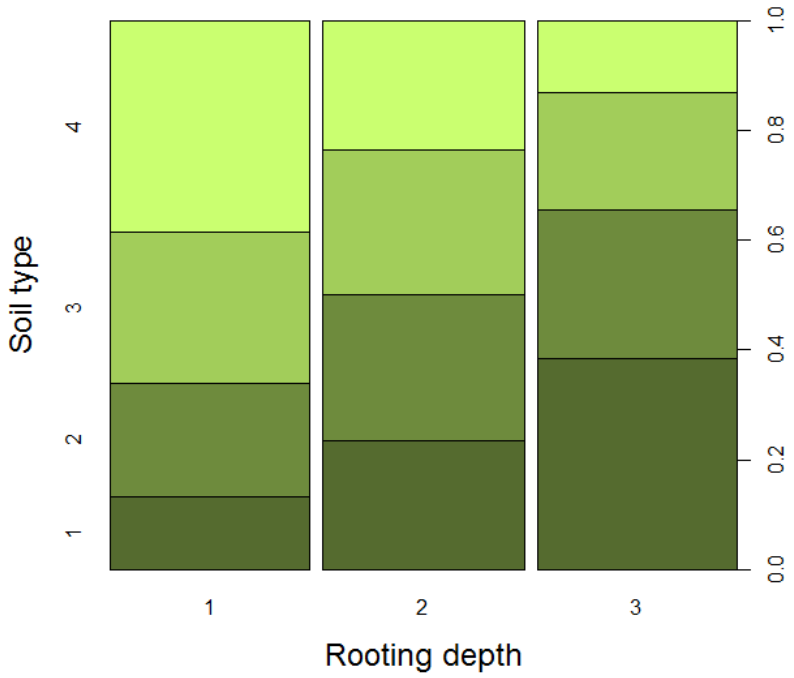


Figure 2: Distribution of the levels of Rooting depth and Soil type in the generation of the sample for the sensitivity analysis using the copula method. The Pearson correlation coefficient between the two variables is -0.351. Rooting depth levels: 1=shallow; 2=medium; 3=deep. Soil type levels: 1=Freely draining; 2=Gleys; 3=Mineral peats; 4=Deep peats. This Figure shows that the Quasi-random values of Rooting depth and Soil type generated with the method of Sobol' are influenced by the correlation structure of the copula. E.g.: for shallow Rooting depth (level: 1), the likelihood of a Soil type "Deep peats" (level: 4) is higher than that the other types of soil. For deep Rooting depth (level: 3), the likelihood of a Soil type "Freely draining" (level: 1) is higher than that of the other types of soil. For medium Rooting depth (level: 2) all Soil types are almost equally likely to be selected with the Quasi-random number generator under the correlation structure of the copula.

2.2.5 ForestGALES simulations

From the samples generated for each of the three species, we used ForestGALES to calculate two sets of outputs, $CWS_{(B, O)}$ and $Prob_{(B, O)}$. Because of the structure of the model, and the nature of the outputs, we performed different analyses on the two sets of outputs, as described below.

2.2.5.1 Sensitivity analysis of the output: Critical wind speeds

In order to investigate what variables the model users should focus on knowing more accurately to maximally reduce uncertainty in the model's predictions of CWS for each species, we applied the SA Factor Prioritisation (FP) setting. Following this setting, data collection of the variables with the largest S_i should be prioritised for reducing the uncertainty of the inputs and optimising predictions calculated with ForestGALES. Conversely, to identify those variables which negligibly contribute to the variance of the CWS, we adopted the SA setting Factor Fixing (FF), which is based on S^T_i. When the S^T_i of a variable was found to be close to zero, we fixed that variable to different values within its range, and re-ran the simulations with ForestGALES, while maintaining the variation in all the other variables. For discrete variables, we explored all the possible values. For continuous variables, we

focussed on the minimum, maximum, and mean values. We then compared the original $CWS_{(B, O)}$ with those calculated after fixing a non-influential variable using scatterplots. We used the method of Sobol' et al. (2007) for the estimation of the approximation error when fixing non-influential variables. The authors have shown that for orthogonal (i.e. non-correlated) variables, the approximation error when fixing uninfluential variables is equal to twice the value of the S^T_i of the uninfluential variables, and that it also applies to groups of variables. In the case of multiple non-influential variables, we repeated these procedures for all the combinations of the values of the relevant variables.

2.2.5.2 Sensitivity analysis of the output: Probabilities of damage

For $Prob_{(B, O)}$ we applied the Factor Mapping (FM) setting of SA, which is based on Regionalised Sensitivity Analysis (e.g. Hornberger and Spear, 1981), a procedure belonging to the family of Monte Carlo Filtering methods. We divided the output space in a behavioural region and a non-behavioural region, setting the threshold at $Prob_{(B, O)} = 0.1$ (i.e. a 10% probability of damage) to differentiate between endemic and catastrophic wind damage (Mitchell, 1998). That is, when the calculated $Prob_{(B, O)}$ were smaller than 0.1, we assigned the model run to the corresponding behavioural regions, and to the non-behavioural ones otherwise. We mapped the outputs to the values of the input variables, and investigated the sensitivity of ForestGALES to DAMS, and to the other inputs that were flagged as influential in the calculations of the respective CWS. In fact, DAMS is the only input variable directly involved in the wind climate model, and logically a non-influential variable for the calculation of $CWS_{(B,O)}$ cannot drive variation in the corresponding $Prob_{(B, O)}$. To investigate the sensitivity of the wind climate module to these variables, we plotted their marginal cumulative distribution functions (CDF) conditional on the behavioural and non-behavioural realisations of the model. We estimated the sensitivity of the model to these variables with Smirnov two-sample (two sided) tests, which determine the significance of the differences between the behavioural and non-behavioural CDFs (Saltelli et al., 2008). In order to investigate the second order interactions between these variables, we used two-dimensional density plots to identify the regions in the bivariate input space that are more likely to result in behavioural or non-behavioural realisations of ForestGALES.

2.2.6 Differences between species

Species is used in ForestGALES as a trigger to activate the corresponding sub-modules where a number of tree characteristics such as canopy dimensions are calculated. Similarly, the values of C_{reg} for different combinations of soil type and rooting depth, the species-specific values of the density of green wood, and the Modulus of Rupture and the Modulus of Elasticity of green wood, are stored in these sub-modules. To explore whether differences between species exist in the ranking of the variables that drive most of the variance in $CWS_{(B,O)}$, we used a ranking method based on Savage scores (Savage, 1956). Coefficients of concordance were used as described by Iman and Conover (1987) and Helton et al. (2005) to compare the importance ranking of input variables between species. For each species, the *m* input variables are ranked in order of their importance (expressed as their S^T_i), reversely in comparison to the procedure used in standard rank regressions; that is, the variable with the highest S^T_i is given a rank $r(S^T_i)$ of 1, the variable with the second highest S^T_i a rank

of 2, and so on. This procedure is often used to calculate Kendall's coefficients of concordance (KCC), which assign equal weight to each rank. However, because the purpose of a sensitivity analysis is to identify the most important variables (i.e. those with the top ranks), KCC are inappropriate (Helton et al., 2005). Therefore, the ranks are replaced by the corresponding Savage scores to emphasise the importance of the top ranks, as described in Iman and Conover (1987). For this, we have adopted Eq. (6), adapted from Helton et al. (2005).

$$ss(S_i^T) = \sum_{j=r(S_i^T)}^{m} {}^{1}/_{j} \quad (6)$$

where *ss(.)* indicates the Savage scores of variable X_i, and the *m* variables in the model are ranked in descending order of importance according to their S^T_i. In the present study $m = 6$, as species is the variable under scrutiny here. Averages are calculated in the event of ties (Iman and Conover, 1987). This substitution allows the calculation of the top-down coefficient of concordance amongst all species (C_T), with Eq. (7), adapted from Iman and Conover (1987) and Helton et al. (2005):

$$C_T = \left\{\sum_{j=1}^{m}\left[\sum_{q=1}^{nS} ss_q(S_i^T)\right]^2 - nS^2m\right\} \Big/ \left\{nS^2\left(m - \sum_{j=1}^{m} {}^{1}/_{j}\right)\right\} \quad (7)$$

where *nS* is the number of species (here, $nS = 3$). To calculate a value of correlation amongst all the species we used an index developed by Iman and Conover (1987). The authors showed that

$$T_{all} = nS(m-1)C_T \quad (8)$$

follows a chi-square distribution with ($m - 1$) degrees of freedom, with the subscript "*all*" indicating a value of correlation amongst all the species. Hence, a comparison between T_{all} and a chi-square distribution with d.f. = 5 provides a *p*-value to test the null hypothesis of independence of the importance rankings of the input variables between different species. That is, a small *p*-value would prompt us to reject the null hypothesis, and would indicate that the rankings of the most important input variables are similar between species.

In order to delve further into the differences between pairs of species, a similar test was carried out with Pearson correlation coefficients adapted for Savage scores when $nS = 2$, as shown by Iman and Conover (1987). For each pairing of species α and β, Savage scores were applied to the rankings of their S^T_i with Equation (6). The top-down coefficient of concordance between each pair was then calculated with Eq. (9), adapted from Iman and Conover (1987) and Helton et al. (2005).

$$r_T = \left(\sum_{j=1}^{m} ss_{\alpha_j} ss_{\beta_j} - m\right) \Big/ \left(m - \sum_{j=1}^{m} {}^{1}/_{j}\right) \quad (9)$$

where $ss_{\alpha j}$ and $ss_{\beta j}$, (j = 1,…,*m*) are the Savage scores for the rankings of the *m* S^T_i for species α and β, respectively. The significance of the differences between each pair of species is then evaluated against a chi-square distribution with ($m - 1$) degrees of freedom, using an adaptation of Eq. (8).

$$T_{\alpha,\beta} = 2(m-1)r_T \quad (10)$$

3. Results

The Results section is divided in three parts: the first one shows the results of the GSA for the $CWS_{(B,O)}$ calculated in the GALES module. The second part shows the similarities in ranking of sensitivity indices between species. The third part describes the GSA results for the $Prob_{(B,O)}$ calculated with the wind climate module. In the first and third parts the three species are presented one at a time.

3.1 Critical Wind Speeds – Sensitivity in the GALES module

Throughout this section, we first show the results for *P. sitchensis*, followed by *P. pinaster*, and lastly *E. globulus*. We then introduce the results of the Factor Fixing setting.

3.1.1 Picea sitchensis

For *P. sitchensis*, the sensitivity of the GALES module to the input variables summarised in Table 2 (DAMS aside) is shown in Figure 3. The Sobol' sensitivity indices are shown for $CWS_{(B,O)}$.

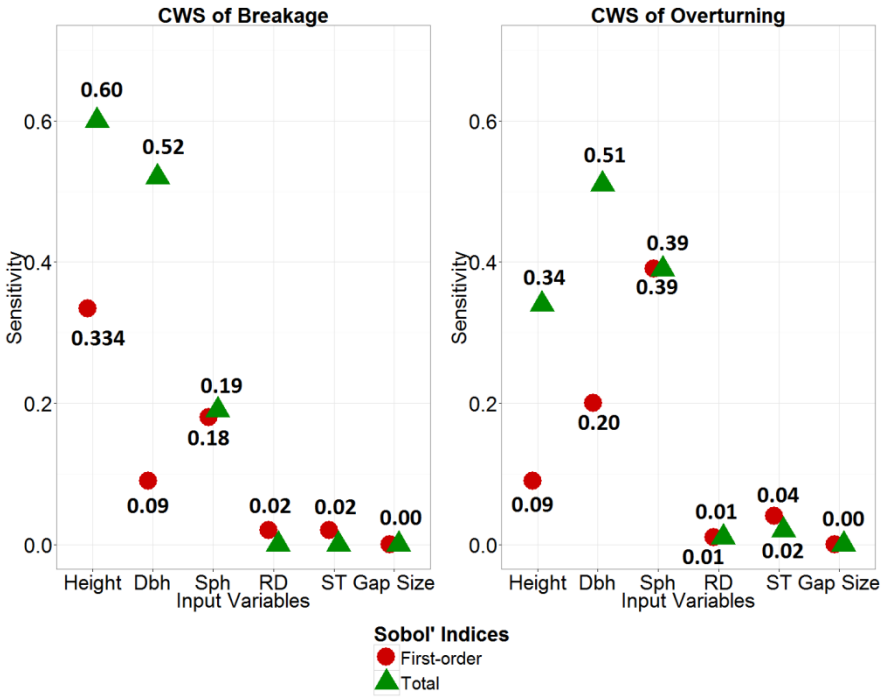


Figure 3: Sobol' first-order and total sensitivity indices for the critical wind speeds for breakage and overturning for *P. sitchensis*. Dbh: diameter at breast height; Sph: stems per hectare. RD: rooting depth. ST: soil type. The total indices of RD, ST, and Gap size for CWS_B are 0.00. The total index of Gap size for $CWS_{(B,O)}$ is 0.00.

As seen in Figure 3, Tree height, *dbh*, and *Sph* are the variables to which the $CWS_{(B,O)}$ are most sensitive, although their importance ranking differs between the two CWS, as shown by their S^T_i. The large differences between the S^T_i (green triangles) and S_i (red circles) of Tree height and *dbh* indicate that these variables are involved in a large number of interactions with other variables, for both breakage and overturning. Seen that the S^T_i of the other variables are never significantly larger than their S_i, these interactions are mainly between Tree height and *dbh* themselves. As expected, Rooting depth and Soil type do not contribute to the variation of CWS_B. These two variables are only marginally influential with regards to CWS_O, with Rooting depth being more important than Soil type. The size of an upwind green edge Gap is uninfluential to the calculations of $CWS_{(B,O}$

3.1.2 Pinus pinaster

Figure 4 shows the indices of Sobol' for *P. pinaster*.

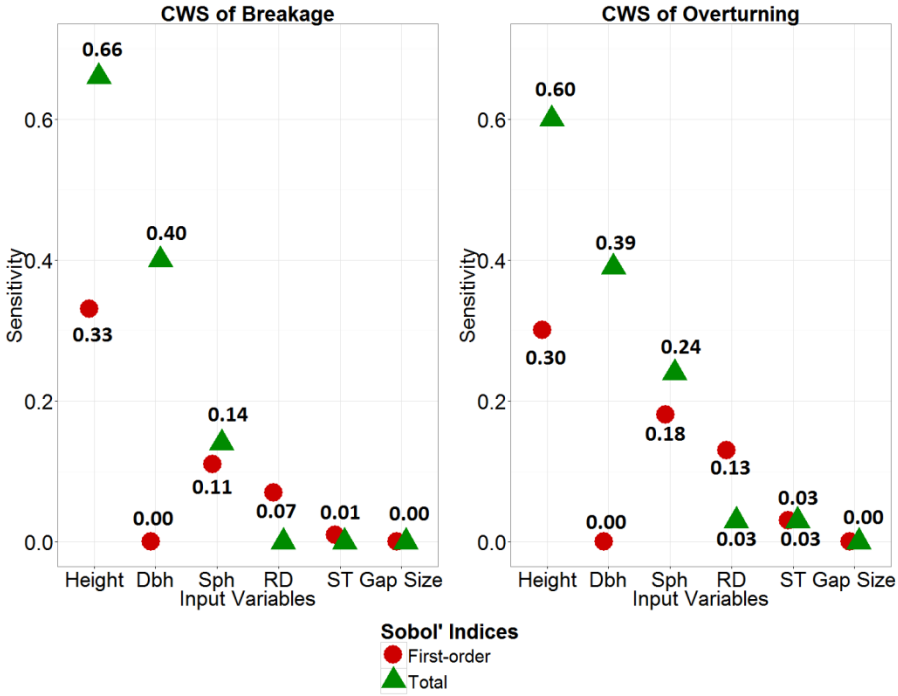


Figure 4: Sobol' first-order and total sensitivity indices for the critical wind speeds for breakage and overturning for *P. pinaster*. Dbh: diameter at breast height; Sph: stems per hectare. RD: rooting depth. ST: soil type. The total indices of RD, ST, and Gap size for CWS_B are 0.00. The total index of Gap size for CWS_O is 0.00.

Figure 4 shows that, for *P. pinaster*, the most influential variables are, in decreasing order: Tree height, *dbh*, and *Sph*, for both CWS. The large differences between the S^T_i and S_i seen for *P. sitchensis* are found also for *P. pinaster*, indicating large interactions. *Sph* is likely to participate more prominently than for *P. sitchensis*, as its S^T_i is slightly larger than its S_i, especially for CWS_O. Rooting depth's S_i for CWS_B is marginal (0.07), suggesting that the moderate correlation with the highly

influential Tree height (0.22, see Table 4) is responsible for this non-zero value. For CWS_O, Rooting depth is more influential than Soil type. Gap size is not influential for either CWS.

3.1.3 Eucalyptus globulus

Figure 5 shows the indices of Sobol' for *E. globulus*.

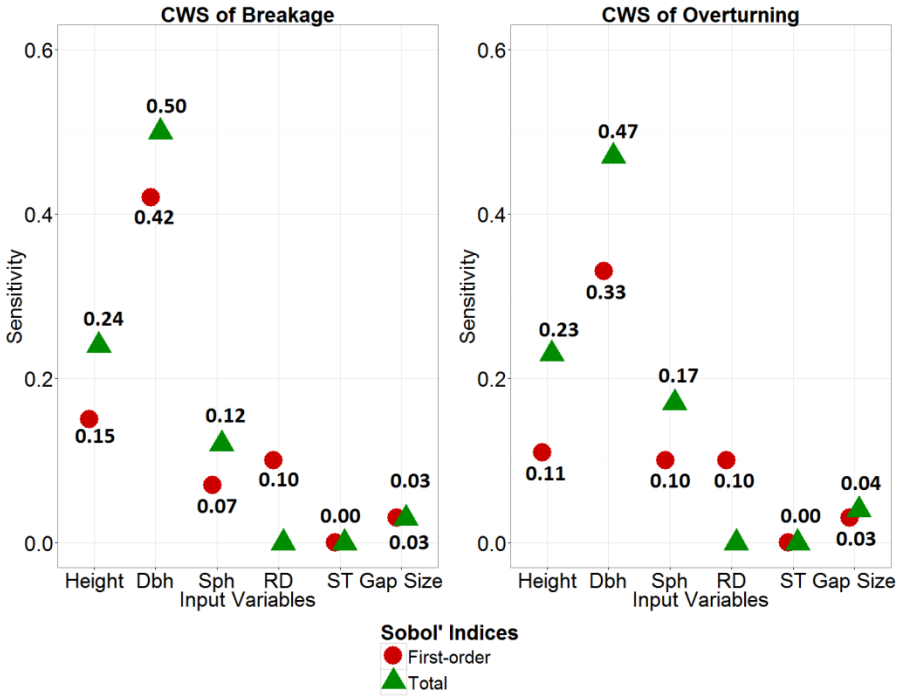


Figure 5: Sobol' first-order and total sensitivity indices for the critical wind speeds for breakage and overturning for *E. globulus*. Dbh: diameter at breast height; Sph: stems per hectare. RD: rooting depth. ST: soil type. The total indices of RD, and ST for CWS_B and for CWS_O are 0.00.

As seen in Figure 5, the most influential variables for *E. globulus* are, in decreasing order: *dbh*, Tree height, and *Sph* for both CWS. The differences between the S^T_i and S_i seen for the other two species are less pronounced for *E. globulus*, indicating somewhat smaller interactions. As for *P. pinaster*, *Sph* is likely to participate in the interactions for *E. globulus*, as its S^T_i is slightly larger than its S_i, especially for CWS_O. The S_i for Rooting depth for both $CWS_{(B,O)}$ are small but significant (0.10). For CWS_B, this is larger than for *Sph*. For CWS_O, Rooting depth has the same S_i value of Tree height and just smaller than that of *Sph* for CWS_O. This is partially attributable to the correlations between Rooting depth and the influential variables Tree height and *dbh*, and perhaps to a numerical imprecision in the estimation of Rooting depth's S_i. In fact, the C_{reg} values in the Rooting depth vs Soil type matrix for *E. globulus* are all equal (i.e. Rooting depth and Soil type function as constants for *E. globulus*). This is because tree-pulling for this species was only performed on one site with a homogeneous soil, and no significant differences were found between C_{reg} values for different rooting depths (Locatelli et al., 2016). This is reflected in the S_i values of Soil type for $CWS_{(B,O)}$ (0 in both cases). Gap size is more influential for both CWS than for the previous two species.

3.1.4 Fixing uninfluential variables

Despite the moderate correlation between Rooting depth and Soil type (-0.35, see Table 4), we calculated the average approximation errors when the three uninfluential variables are fixed on a nominal value, using the method of Sobol' et al. (2007). This method has only been tested for non-correlated variables; therefore the error estimate might not be entirely accurate. The errors are shown in Table 5.

Table 5. Average approximation errors in the calculations of the critical wind speeds when fixing Rooting depth, Soil type, and Gap size

	P. sitchensis		*P. pinaster*		*E. globulus*	
	CWS_B	CWS_O	CWS_B	CWS_O	CWS_B	CWS_O
Rooting depth	0%	2%	0%	6%	0%	0%
Soil type	0%	4%	0%	6%	0%	0%
Gap size	0%	0%	0%	0%	6%	8%

For *P. sitchensis*, fixing Rooting depth or Soil type to a value within their range would result in an average approximation error of 2% and 4%, respectively, of CWS_O. If Rooting depth and Soil type were completely non-correlated, fixing both variables would therefore cause an approximation error of 6%. For *P. pinaster*, fixing Rooting depth and Soil type would result in a 6% average approximation error for CWS_O, and potentially a 12% cumulative error if both were fixed. Lastly, for *E. globulus*, as expected fixing Rooting depth and Soil type would have no average approximation error for $CWS_{(B,O)}$, while fixing Gap would result in a 6% and 8% errors for CWS_B and CWS_O, respectively. The lack of correlation between Gap size and the other input variables ensures the reliability of this estimate.

Because the S^T_i of Rooting depth, Soil type, and Gap size are practically zero for both CWS, we re-ran the simulations with ForestGALES using the same dataset apart from the values of these variables, which were fixed one at a time to different values within their range. For Rooting depth and Soil type, these are the discrete values in Table 3. For Gap size, we chose 0m, 2 times Tree height, 1000m, and 10 times Tree height. The latter was chosen because ForestGALES contains a trap in its code by which an upwind gap cannot be larger than that. We chose to fix Gap size to 2 times Tree height because Gardiner et al. (1997) have shown that it corresponds to the limit of the increase in bending moment coefficient with increasing Gap size. The scatterplots for Rooting depth and Soil type investigated one at a time are shown, for the three species and both CWS, in the Appendix. We anticipate here that the effect of these two variables on CWS_B was confirmed as null by the scatterplots shown in the Appendix. For this reason, in this section we limit ourselves to showing the scatterplots for Gap size alone, and for combinations of values of Rooting depth and Soil type, for Gap size fixed at 10 times Tree height. For Gap size, we show the scatterplots for both CWS because, despite not being numerically identified as influential by our GSA, it shows some influence on $CWS_{(B,O)}$. For Rooting depth vs Soil type, we show the effect of fixing them for CWS_O alone. Figures 6 and 7 show the Gap size scatterplots for $CWS_{(B,O)}$ for the three species.

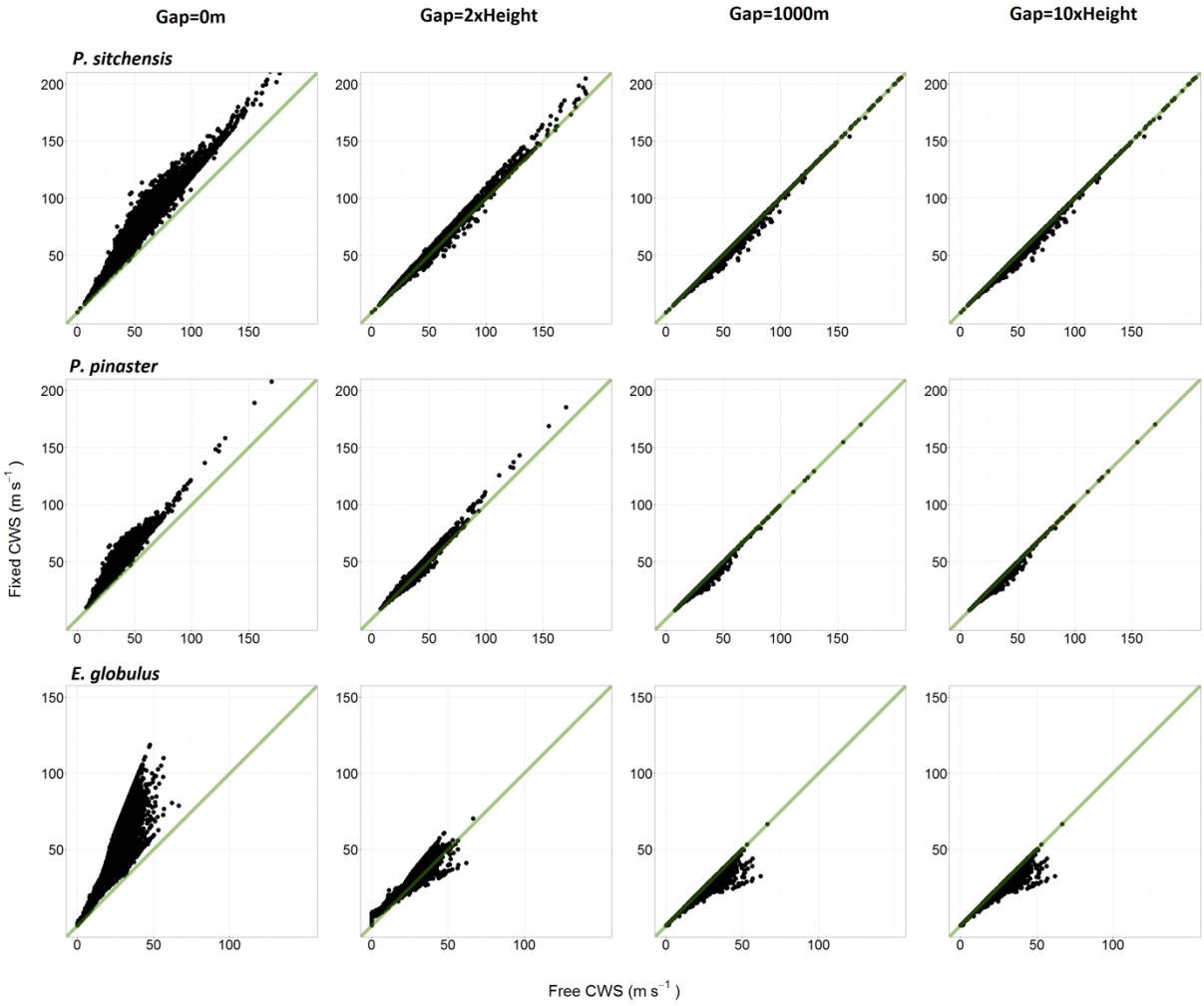


Figure 6: Scatterplots of critical wind speed for breakage for Gap size allowed to vary within its range vs Gap size fixed at four different values. Free: all variables allowed to vary within their ranges; Fixed: Gap size fixed at one of the following values: Gap=0m, Gap size fixed at 0m; Gap=2xHeight, Gap size fixed at 2 times Tree height; Gap=1000m, Gap size fixed at 1000m; Gap=10xHeight, Gap size fixed at 10 times Tree height. The green diagonal line represents the slope through origin [0; 0], i.e.a 1:1 relationship between the results.

Despite the S^{T}_{i} of Gap size being null for *P. sitchensis* and *P. pinaster*, the effect of fixing Gap is evident for all the species, especially when Gap size is fixed at 0m. Fixing Gap size to 0m results in a marked overestimation of CWS_B. Fixing Gap size to 2 times Tree height results in minor overestimation of CWS_B for *P. sitchensis* and *P. pinaster*, while the effect on *E. globulus* is more complex, with equal probabilities of over and underestimation of CWS_B. Fixing Gap size at 1000m or 10 times Tree height has the same result of underestimating CWS_B. The latter is particularly evident

for low to medium CWS_B, which correspond to the area of higher wind risk for a forest. The effect of Gap size on CWS_B is more pronounced for *E. globulus*, which is consistent with the approximation error shown in Table 5.

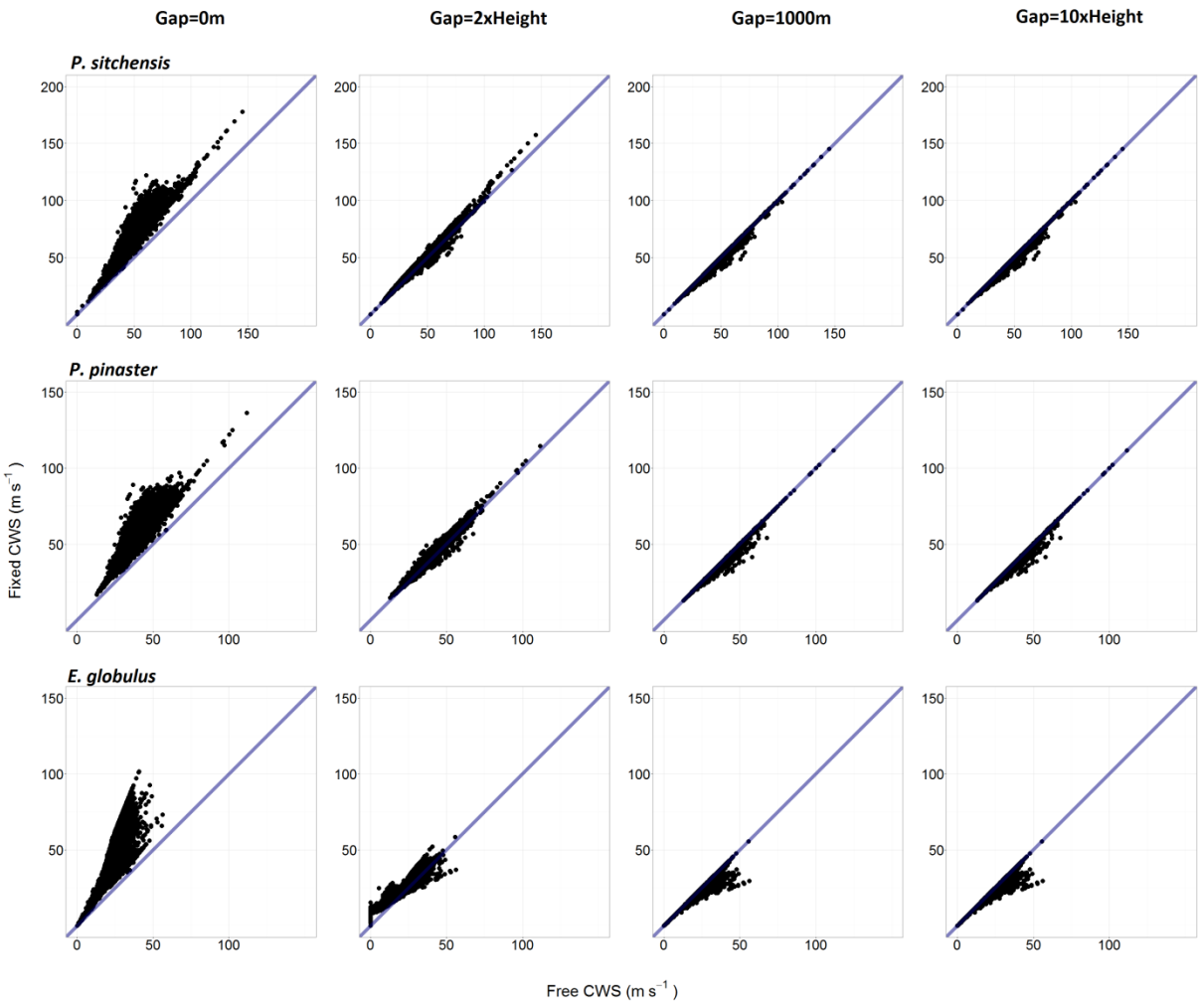


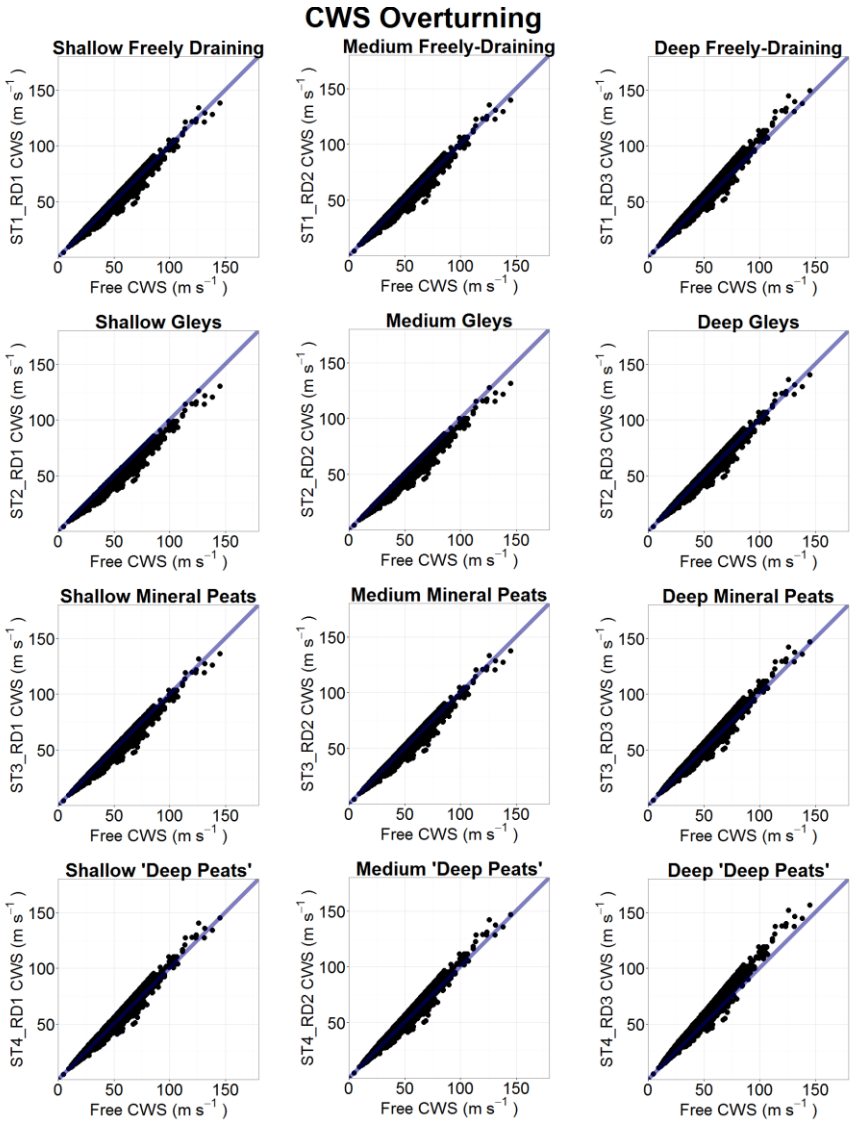
Figure 7: Scatterplots of critical wind speed for overturning for Gap size allowed to vary within its range vs Gap size fixed at four different values. Free: all variables allowed to vary within their ranges; Fixed: Gap size fixed at one of the following values: Gap=0m, Gap size fixed at 0m; Gap=2xHeight, Gap size fixed at 2 times Tree height; Gap=1000m, Gap size fixed at 1000m, Gap=10xHeight: Gap size fixed at 10 times Tree height. The green diagonal line represents the slope through origin [0; 0], i.e.a 1:1 relationship between the results.

The scatterplots in Figure 7 show the effect of fixing Gap size on CWS_O. The plots mirror those for CWS_B shown in Figure 6, with the difference that the range of damaging wind speeds is smaller for overturning than for breakage. For *E. globulus*, fixing Gap size at 2 times Tree height results in a pattern even more complex for CWS_O than for CWS_B, as also very low values are affected. Next, we present the results of fixing Rooting Depth and Soil type, one species at a time.

590 *P. sitchensis:*

591 Figure 8 shows the *P. sitchensis* CWS_O scatterplots for the different levels of Rooting depth and Soil
592 type, with Gap size fixed at 10 times Tree height.

593



594

595

596 Figure 8: Scatterplots of critical wind speed for overturning for *P. sitchensis*. Simulations with variation in all the inputs vs
597 simulations where Rooting depth and Soil type were fixed at a value within their range. Gap size fixed at 10 times tree
598 height. The blue diagonal lines represent the slope through origin [0; 0], i.e. a 1:1 relationship between the results. "Free"
599 on the abscissa indicates simulations for which all variables were allowed to vary within their range. The coding for the
600 ordinate axis indicates the values at which Soil type (ST) and Rooting depth (RD) were fixed. E.g. "ST1_RD1" indicates Soil
601 type 1 (Freely draining) and Rooting depth 1 (Shallow).

602

603 Fixing Rooting depth at "deeply rooted" results in slight overestimations of the CWS_O (i.e. the cloud
604 of points shifts upwards), regardless of Soil type. The same effect is obtained when fixing Soil type at
605 "Freely Draining" and "Deep Peats", regardless of Rooting depth. Fixing Soil type at "Gleys" and

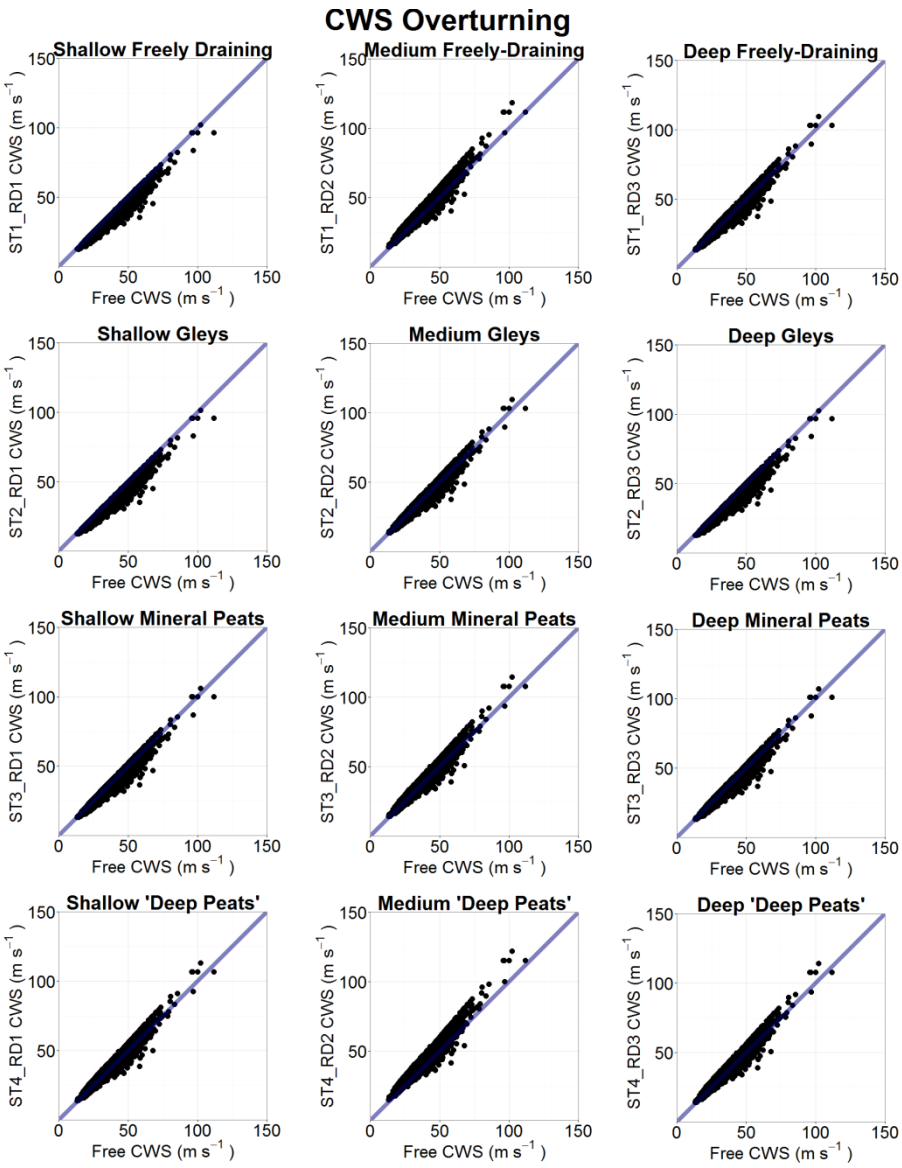
606 "Mineral Peats" results in a slight underestimation of the CWS_O, apart from the already mentioned
607 case of deep Rooting depth. The shape of the clouds of points is partially affected by fixing Gap size
608 (see Figure 7).

609

610 *P. pinaster*

611 Figure 9 shows the scatterplots for CWS_O for *P. pinaster*.

612



613

614 Figure 9: Scatterplots of critical wind speed for overturning for *P. pinaster*. Simulations with variation in all the inputs *vs*
615 simulations where Rooting depth and Soil type were fixed at a value within their range. Gap size fixed at 10 times tree
616 height. The blue diagonal lines represent the slope through origin [0; 0], i.e.a 1:1 relationship between the results. "Free"
617 on the abscissa indicates simulations for which all variables were allowed to vary within their range. The coding for the
618 ordinate axis indicates the values at which Soil type (ST) and Rooting depth (RD) were fixed. E.g. "ST1_RD1" indicates Soil
619 type 1 (Freely draining) and Rooting depth 1 (Shallow).

The scatterplots in Figure 9 show the effect of fixing Gap size, Rooting depth and Soil type on CWS_O calculated for *P. pinaster*. As for *P. sitchensis*, the effect is mainly visible at medium to high CWS_O. In fact, for both species the S^T_i and the average approximation error of Gap size (Table 5) are similar. As shown in Figure 7, fixing Gap size to values other than 0m has the same effect as for *P. sitchensis*, causing an underestimation of CWS_O. Fixing Rooting depth at "medium rooted" results in slight overestimations of the CWS_O, regardless of Soil type. Simulations where Soil type was fixed at "Deep Peats" show a slight overestimation of the CWS_O regardless of Rooting depth, while the simulations where Soil type was fixed at "Gleys" show a slight underestimation of the CWS_O (excluding the case of medium Rooting depth).

E. globulus

Figure 10 shows the scatterplots for CWS_O for *E. globulus*, comparing "Free" simulations with "Fixed" simulations. Gap sized was fixed at 10 times Tree height, as for the previous species.

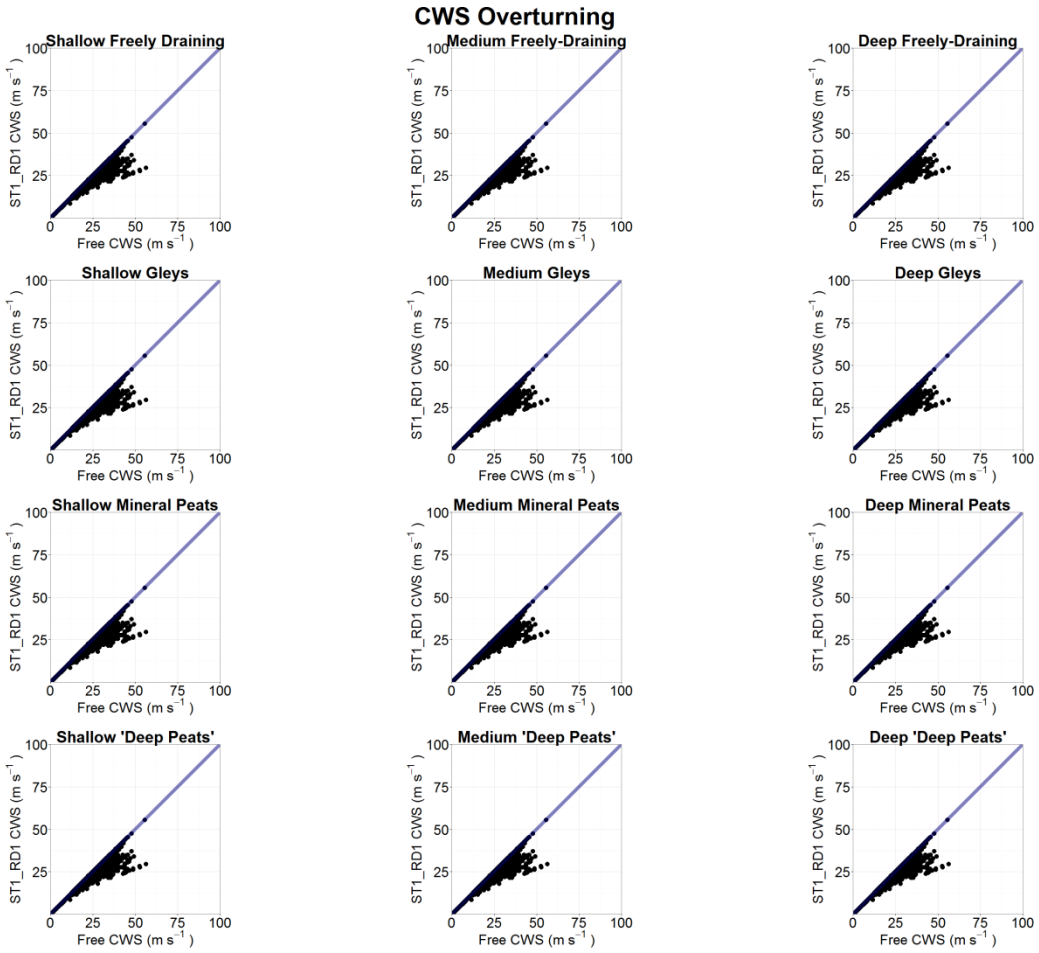


Figure 10: Scatterplots of critical wind speed for overturning for *E. globulus*. Simulations with variation in all the inputs *vs* simulations where Rooting depth and Soil type were fixed at a value within their range. Gap size fixed at 10 times tree height. The blue diagonal lines represent the slope through origin [0; 0], i.e. a 1:1 relationship between the results. "Free"

on the abscissa indicates simulations for which all variables were allowed to vary within their range. The coding for the ordinate axis indicates the values at which Soil type (ST) and Rooting depth (RD) were fixed. E.g. "ST1_RD1" indicates Soil type 1 (Freely draining) and Rooting depth 1 (Shallow).

The scatterplots in Figure 10 confirm that fixing Rooting depth and Soil type has no effect on CWS_O calculated for *E. globulus*, as expected from the lack of variability in the soil parameters. In fact, these plots are identical to those for overturning for different values of Gap size, as shown in Figure 5, as they are entirely driven by the error in fixing Gap size.

3.2 Differences between species

Table 6 shows the *p*-values of the comparisons between the coefficients of concordance for all the species (T_{all}), and for pairs of species ($T_{\alpha,\beta}$), and a chi-square distribution with d.f. = 5. Small *p*-values indicate that the null hypothesis of independence of the importance rankings of the input variables between different species can be rejected, i.e. that the rankings of the most important variables are similar across the three species. Conversely, large *p*-values indicate that the rankings are significantly different between species. Rankings are based on S^T_i values.

Table 6: Significance of correlation between rankings of S^T_i of different species. The H_0 is of independence of rankings between species. Low *p*-values suggest the H_0 should be rejected (i.e. high *p* -values suggest independence of S^T_i rankings between species).

	CWS_B	**CWS_O**
All species	0.029	0.044
P. sitchensis / *P. pinaster*	0.087	0.448
P. sitchensis / *E. globulus*	0.247	0.128
P. pinaster / *E. globulus*	0.247	0.273

As shown in the first row of Table 6, the *p*-values for the comparison between all the species suggest that the rankings of the influential variables for $CWS_{(B,O)}$ are similar for *P. sitchensis*, *P. pinaster*, and *E. globulus*. In fact, as seen in Figures 3, 4, and 5, for the three species the top three ranks of the total Sobol' indices are shared between Tree height, *dbh*, and *Sph*, although not in the same order for all species and for both types of damage (breakage and overturning). The species-specific differences in the ranking of these three variables are mostly responsible for the large *p*-values for the pairwise comparisons. As shown by Iman and Conover (1987), the calculation of the top-down coefficient of concordance amongst all species (C_T) is strongly driven by agreement between the top ranks. This can be seen in the calculation of the Savage scores with Eq. (6). The importance of at least a degree of accordance between the top three ranks in driving the calculation of the T_{all} index is further corroborated by the numerator of Eq. (7): the more similar the top ranks are amongst species, and the larger the number of species, the larger C_T (and therefore T_{all}) becomes. As a result, the probability of the T_{all} index to be larger than the upper-tail critical value of a chi-square distribution (in our case, with 5 degrees of freedom) diminishes as C_T and T_{all} increase.

With regards to the pairwise comparisons between our species, certain differences are evident. For CWS_B, the ranking of the S^T_i of *E. globulus* is markedly different from the other two (Figures 3, 4, and 5). This is reflected by the *p*-values in Table 6 for the comparisons that include *E. globulus* being the largest (0.247), while the *p*-value of the comparison between *P. sitchensis* and *P. pinaster* (0.087) indicates that differences between these two species are almost non-significant at the 95% confidence interval. It should be noted that the fact that the S^T_i rankings of these two species are identical (Figures 3 and 4) suggests that the accuracy of our statistical test is not perfect. For CWS_B, the large *p*-values (0.237 and 0.246) for the comparisons between *P. sitchensis* / *E. globulus*, and *P. pinaster* / *E. globulus*, are driven by the fact that the ranking of the top two variables, Tree height and *dbh*, are inverted between the pair (*P. sitchensis*, *P. pinaster*), and *E. globulus*. In fact, the difference between the Savage scores calculated for the top rank, and the second or the third rank, are quite significant (top rank: 2.45; second rank: 1.45; third rank: 0.95), while further ranks, especially in the case of ties (e.g. for Rooting Depth and Soil type) have similar low values, below 0.5. Therefore, in pairwise comparisons a small disagreement at the top three ranks can result in the S^T_i rankings of the 2 species being flagged as substantially different. This is unlike in the calculations of C_T and T_{all}, for which partial agreements between the top S^T_i rankings of the three species contributes to the degree of similarity between all three species. Similarly, the small, but non-zero S^T_i of Gap for *E. globulus* contributes marginally to these pairwise differences that involve *E. globulus*, as its rank is higher than for the other two species. For CWS_O, the difference between *P. sitchensis* and *P. pinaster* (*p*-value 0.448) is due to the different ranks of the top three variables (Tree height, *dbh*, and *Sph*). For the *P. pinaster* / *E. globulus* pair, the large *p*-value (0.273) is due to the rankings of Tree height, *dbh*, and Gap size. Similarly, the difference between *P. sitchensis* and *E. globulus* (*p*-value 0.128) is attributable to the rankings of Tree height, *Sph*, and Gap size.

3.3 Probabilities of damage – Sensitivity in the wind climate module

As stated in the Methods section, we have set the threshold for the probabilities of damage at 10% (i.e. a probability of 0.1), to differentiate between behavioural ($Prob_{(B,O)} < 0.1$) and non-behavioural ($Prob_{(B,O)} > 0.1$) regions. The CDF plot and the 2D density plots throughout this section are based on this categorisation. In the CDF plot, the values of the D-statistic represent the maximum distance between the CDF curves: the larger this statistic is, the further apart the CDF curves are, suggesting that the variable's importance in differentiating between behavioural and non-behavioural realisations of ForestGALES is large We show only the first CDF plot, for $Prob_B$ for *P. sitchensis*, to illustrate the interpretation of the Smirnov test and its D-statistic. The other CDF plots are not shown, while the values of the D-statistic are summarised in Table 7, which will be referenced throughout this section.

3.3.1 Picea sitchensis

Figure 11 shows the CDF plots for *P. sitchensis* for $Prob_B$, for all the ForestGALES input variables.

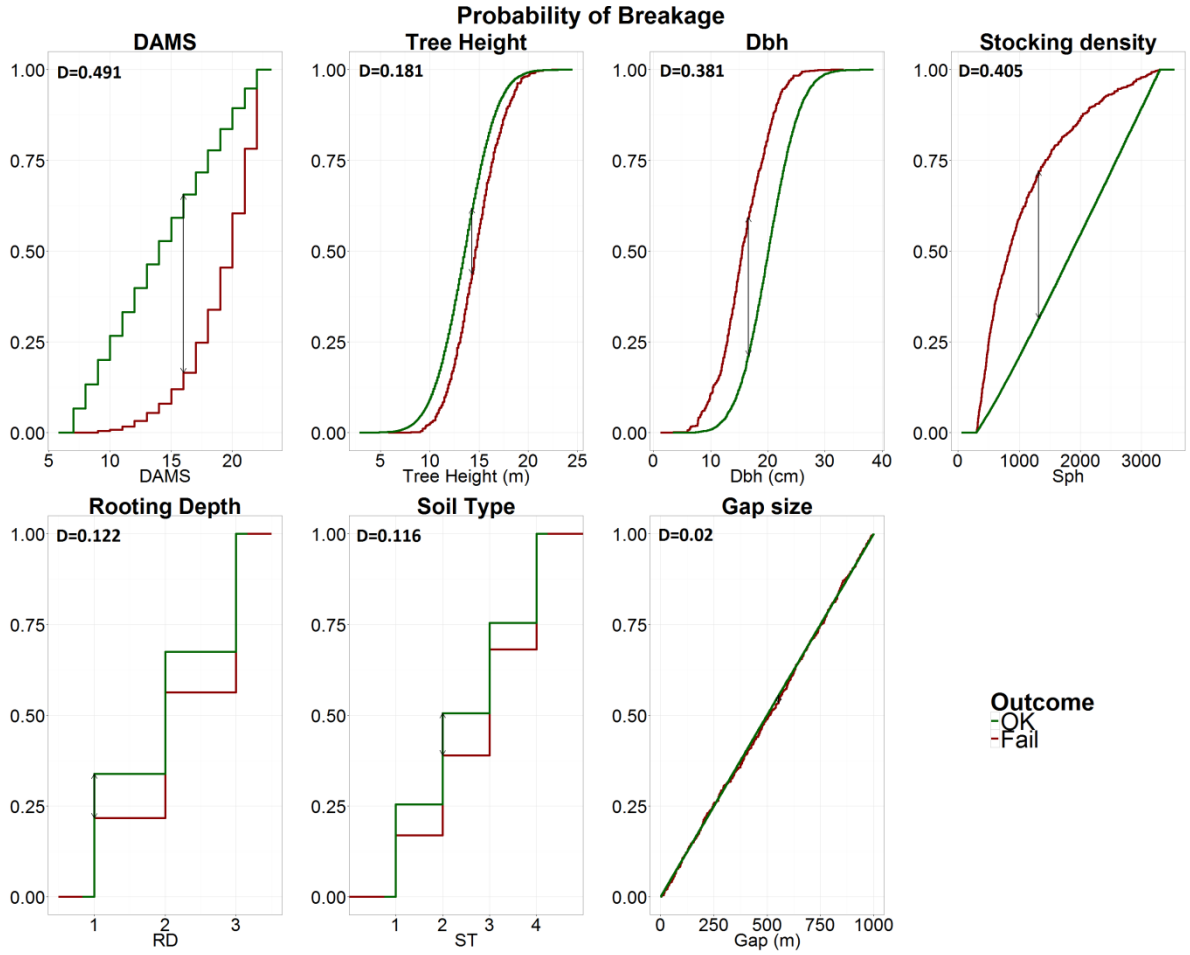


Figure 11: Cumulative density function plots of the probability of breakage for *P. sitchensis*. DAMS: Detailed Aspect Methods of Scoring, a measure of the windiness of the site. Dbh: diameter at breast height; Sph: stems per hectare. The green lines represent model realisation in the behavioural region (probability < 0.1). The red lines represent model realisations in the non-behavioural region (probability > 0.1). The arrows indicate the maximum distance between the cumulative distributions. Large distances indicate that the variable is influential, as described by the values of the D-statistic.

Figure 11 shows that, for *P. sitchensis*, the main drivers of the realisations of ForestGALES in the behavioural and non-behavioural regions of $Prob_B$ are *dbh*, DAMS, and *Sph*, followed by Tree Height, while the other variables contribute only marginally. Rooting depth and Soil type show some importance, which is attributable to their correlation with *dbh* and *Sph*, respectively (see Table 4). The results for $Prob_O$ are shown in Table 7.

730 Table 7: Values of the D-statistic of the Smirnov two-sample (two sided) tests for probabilities of damage (breakage, $Prob_B$;
731 overturning, $Prob_O$). The larger the value of the D-statistic, the more influential a variable is on differentiating between the
732 behavioural (probability of damage < 10%) and non-behavioural (> 10%) realisations of our ForestGALES simulations.

	P. sitchensis		*P. pinaster*		*E. globulus*	
	$Prob_B$	**$Prob_O$**	**$Prob_B$**	**$Prob_O$**	**$Prob_B$**	**$Prob_O$**
DAMS	0.491	0.563	0.584	0.642	0.572	0.648
Tree height	0.181	0.107	0.256	0.321	0.157	0.089
Dbh	0.381	0.392	0.081	0.099	0.294	0.2
Sph	0.405	0.493	0.27	0.373	0.105	0.114
Rooting Depth	0.122	0.087	0.126	0.232	0.135	0.122
Soil Type	0.116	0.113	0.07	0.064	0.017	0.019
Gap size	0.02	0.032	0.014	0.022	0.033	0.041

733

734 As shown in Table 7, for *P. sitchensis*, the variables driving the variation in $Prob_O$ are similar to those
735 of $Prob_B$, with the only difference being that Tree Height is less important than Soil Type. The
736 influence of Rooting depth is smaller than for $Prob_B$, and that of Soil type is very similar for the two
737 probabilities of damage. These results mirror the relative differences between the respective S^T_i for
738 CWS_B and CWS_O, shown in Figure 3.

739 In order to investigate the two-way interactions between influential variables for $Prob_{(B,O)}$, we used
740 2D-density plots. We also include Tree height, despite it being flagged as marginally influential for
741 $Prob_{(B,O)}$, because of its high values of S^T_i and S_i. Figures 12 and 13 show these two-way interactions
742 for *P. sitchensis* for $Prob_B$ and $Prob_O$, respectively. The first three plots (*a* to *c*) show the interactions
743 between DAMS and one of Tree height, *dbh*, and *Sph*. The last three plots (*d* to *f*) show the
744 interactions between these three variables. Irregular shapes are due to the pattern of pseudo-
745 random numbers generated with the Quasi-Monte Carlo method of Sobol' (1990, 1998).

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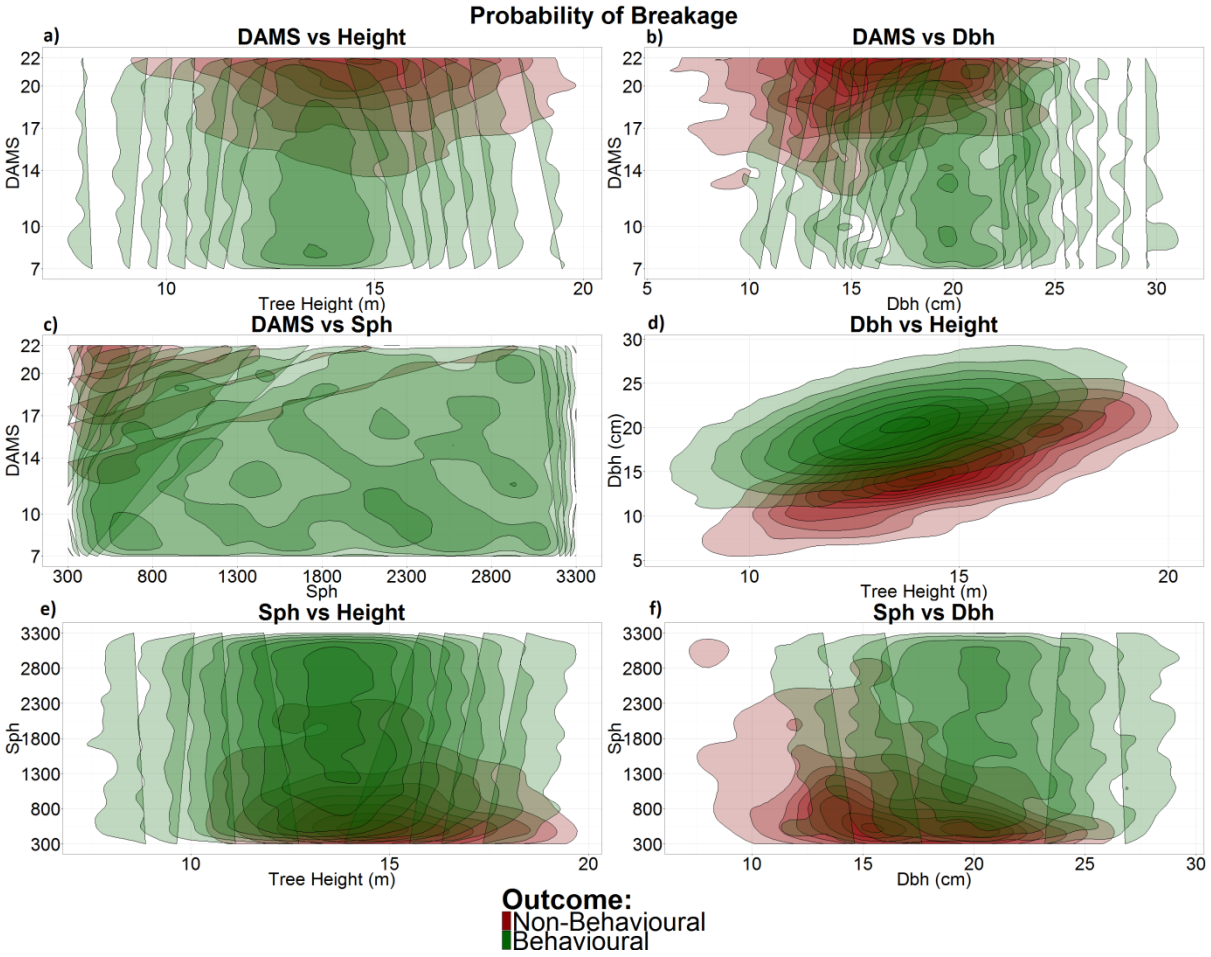

Figure 12: 2D – density plots for probability of breakage for *P. sitchensis*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

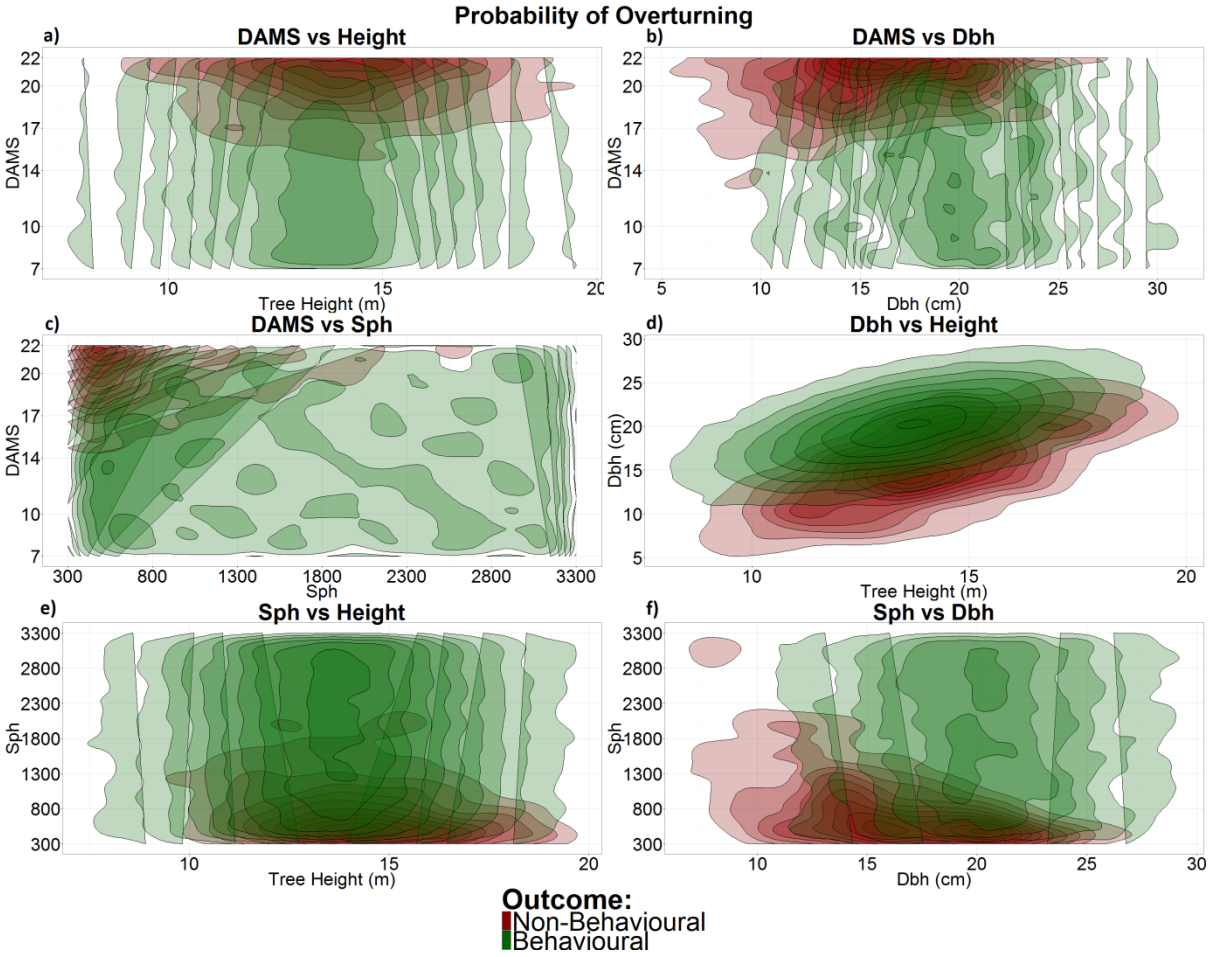

Figure 13: 2D – density plots for probability of overturning for *P. sitchensis*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "Non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

The trends in Figures 12 and 13 are very similar. Most of the plots show large areas where either damage or no damage can result for the same combinations of the variables in the plots (i.e. red and green areas overlap), suggesting that bivariate interactions are not sufficient to discriminate between behavioural ($Prob_{(B,O)} < 0.1$) and non-behavioural ($Prob_{(B,O)} > 0.1$) realisations of ForestGALES. The patterns of green and red areas in both Figures show that for *P. sitchensis* ForestGALES predicts damage for medium-sized trees for exposed sites (DAMS over 12, graphs *a* and *b* in Figures 12 and 13), while shorter trees and trees with a large *dbh* are at less risk of damage. The model predicts that trees with *dbh* above ~25cm will be safe from damage, regardless of the severity of the wind, while trees of small diameters will be prone to damage even at low DAMS (Figures 12*b* and 13*b*). The DAMS vs *Sph* plots show that ForestGALES predicts that the stands most at risk are those of low stocking densities, although areas of higher probabilities of damage are present for other stocking densities (Figure 13*c*). The *dbh* vs Height plots show that the model predicts higher probabilities of damage to trees with small *dbh*, especially for short trees. The *Sph* vs Height plots indicate that, regardless of the height of the trees, ForestGALES predicts more damage to stands with low stocking densities, and higher probabilities of damage for trees taller than 10m. As for the

interaction between *Sph* and *dbh*, ForestGALES predicts more damage to trees of small diameter, especially for stands of low to medium stocking densities (Figures 12*f* and 13*f*).

3.3.2 Pinus pinaster

As shown in Table 7,for *P. pinaster* the most influential variables with regards to $Prob_B$ are DAMS, *Sph*, and Tree height, while the other variables contribute little to the variation in the output. As for *P. sitchensis*, Rooting depth and Soil type show minimal importance, likely attributable to their correlation with Tree height and *Sph*, respectively, as shown in Table 4.

The main drivers of variation of $Prob_O$ for *P. pinaster* are the same as those of $Prob_B$ (in decreasing order: DAMS, *Sph*, Tree height). The value of the D-statistic of Rooting depth is higher for $Prob_O$ (0.232) than for $Prob_B$ (0.126), which reflects the variable's higher S_i for CWS_O than for CWS_B, as seen in Figure 4. In Figures 14 and 15 we show the two-way interactions for *P. pinaster* for the probabilities of breakage and overturning, respectively.

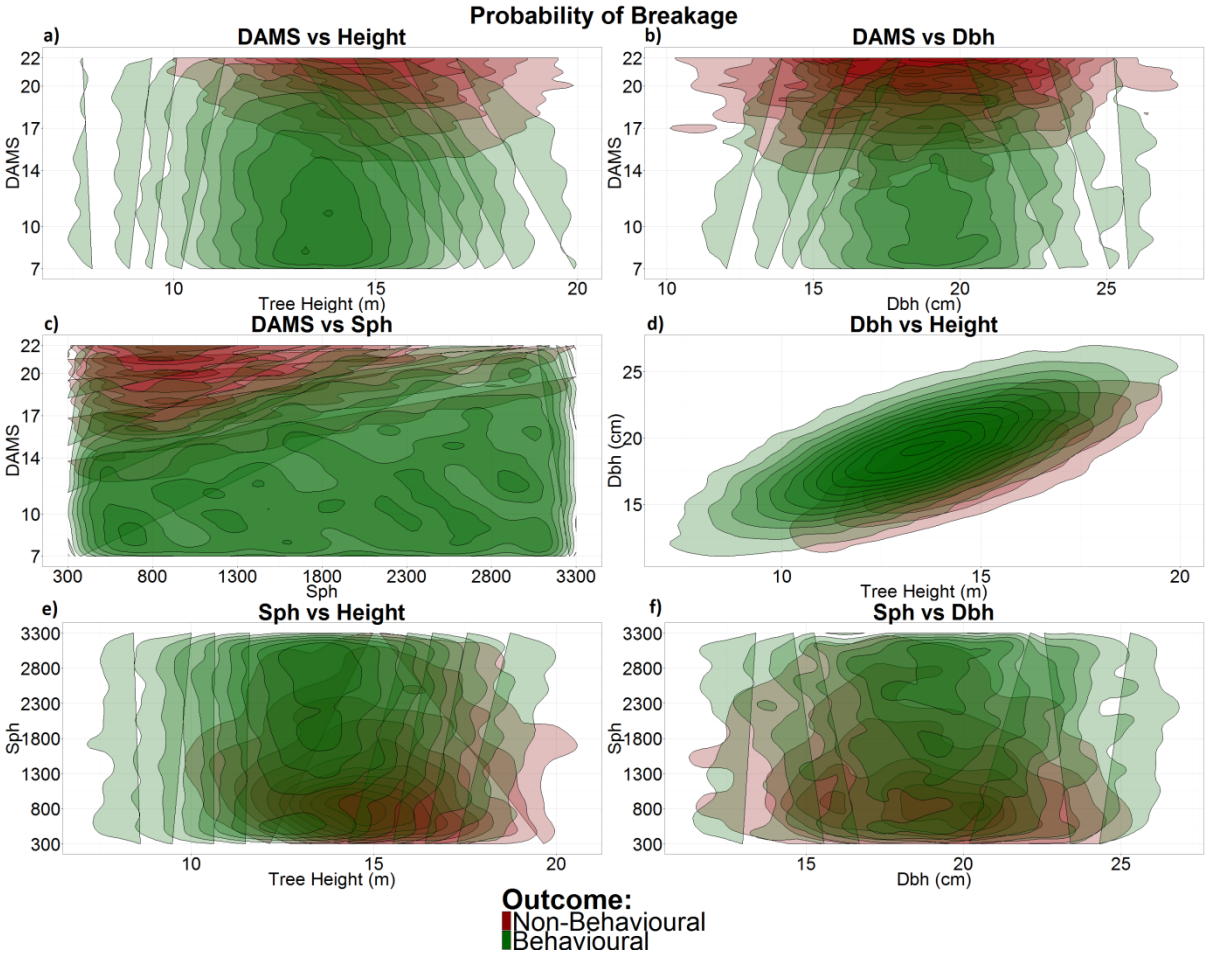

Figure 14: 2D – density plots for probability of breakage for *P. pinaster*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "Non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

The patterns of green and red areas in Figure 14 show that, with regards to the interaction between DAMS and Tree height, ForestGALES predicts that short (<10m) *P. pinaster* trees are safe from breakage, and that DAMS lower than 14 are generally safe (Figure 14*a*). In fact, below this DAMS values, non-behavioural realisations of ForestGALES ($Prob_{(B,O)}$ > 0.1, shown in red), are absent. This threshold is slightly lower (DAMS =13) for *dbh*, whereby larger trees (*dbh* > 24cm) are at low risk of breakage for DAMS up to 20 (Figure 14*b*). As for *P. sitchensis*, low stocking densities are associated with higher probabilities of damage, although ForestGALES predicts damage to *P. pinaster* stands of high densities (up to 3,300 *Sph*) for DAMS as low as 17 (Figure 14*c*). With regards to the interaction between *dbh* and Tree height, ForestGALES predicts that tall trees (height > 11m) are as likely to survive as they are to break, regardless of their *dbh*, while short trees with small to medium *dbh*, and tall trees with large *dbh* are less likely to break (Figure 14*d*). The *Sph* vs Tree height plot shows that short *P. pinaster* trees are at lower risk of breakage regardless of the stocking density of the stand, while tall trees are exposed to a higher risk for low *Sph* (Figure 14*e*). With regards to the interaction between *Sph* and *dbh*, areas of high probability of breakage are widespread in the plot (Figure 14*f*).

However, ForestGALES predicts that large trees at high stocking densities have a lower probability of damage.

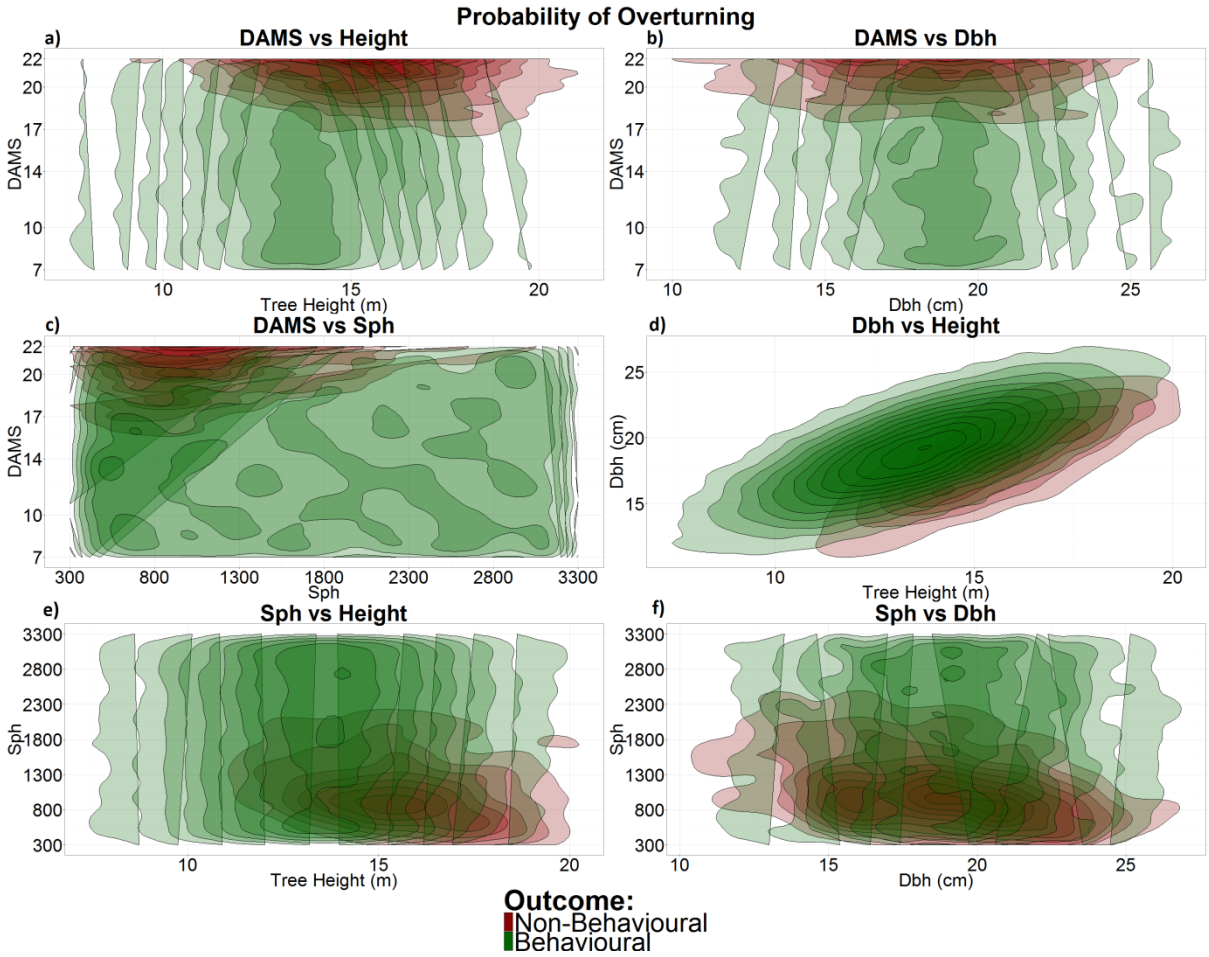

Figure 15: 2D – density plots for probability of overturning for *P. pinaster*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "Non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

The DAMS plots in Figure 15 are considerably clearer than those for $Prob_B$ shown in Figure 14, as the areas that describe high and low probabilities of damage (red and green areas, respectively) are more distinct than those in Figure 14. The plots that show the interactions between Tree height, *dbh*, and *Sph*, are similar to those for $Prob_B$. With regards to overturning, ForestGALES predicts that *P. pinaster* trees above a height of ~10m are likely to fail for DAMS > 17 (Figure 15*a*). Similarly, ForestGALES predicts that *P. pinaster* trees will overturn when exposed to a wind climate corresponding to DAMS > 17, regardless of their *dbh* (Figure 15*b*). The DAMS vs *Sph* plot shows that low stocking densities are at higher risk of overturning for DAMS as low as 11, while DAMS of 20 and above are required to overturn trees in very dense stands. The d*bh* vs Tree height plot (figure 15*d*) is almost identical to that in Figure 14*d*, with trees of height larger than 11m being as likely to survive as to uproot, while short trees are less likely to uproot, regardless of their *dbh*. The interactions between *Sph* and Tree height, and *Sph* and *dbh*, show that higher stocking densities are associated

844 with lower probabilities of overturning, regardless of the height or diameter of the trees. However,
845 short trees (height < 11m) show higher probabilities of survival also at low stocking densities.

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847 *3.3.3 Eucalyptus globulus*

848 As shown in Table 7, for *E. globulus* DAMS is the most important variable for the behavioural and
849 non-behavioural realisations of ForestGALES for $Prob_B$, followed by *dbh* and Tree height. For $Prob_O$,
850 DAMS and *dbh*, and marginally *Sph*, are the most important variables to differentiate between the
851 behavioural and non-behavioural regions of the output space. The correlations shown in Table 4
852 between Rooting depth and these two variables are responsible for the relatively high value of the
853 D-statistic for Rooting depth, and for the non-zero value of that for Soil type, for both $Prob_{(B,O)}$.

854 Figures 16 and 17 show the two-way interactions for *E. globulus* for the probabilities of breakage
855 and overturning, respectively.

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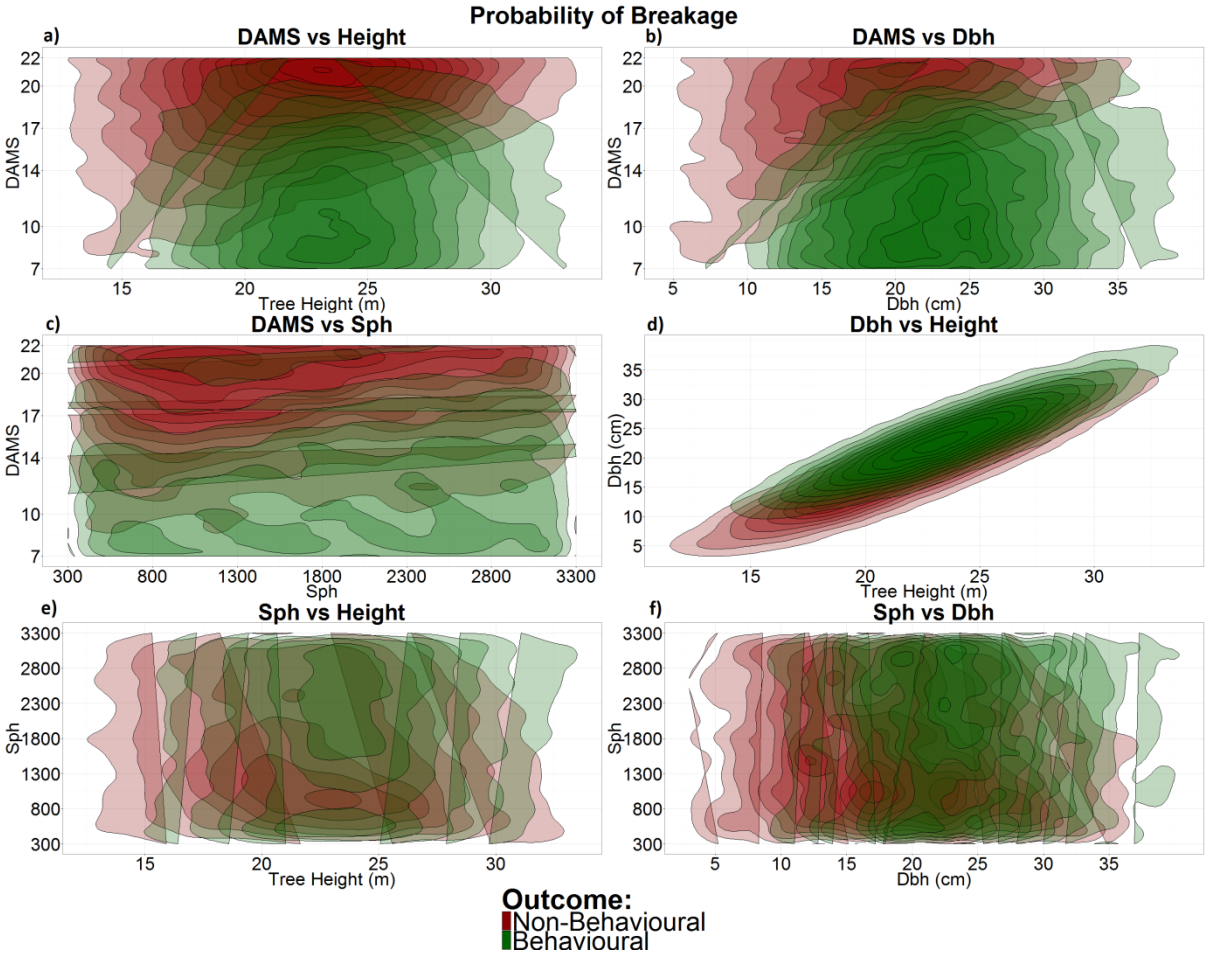

Figure 16: 2D – density plots for probability of breakage for *E. globulus*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "Non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

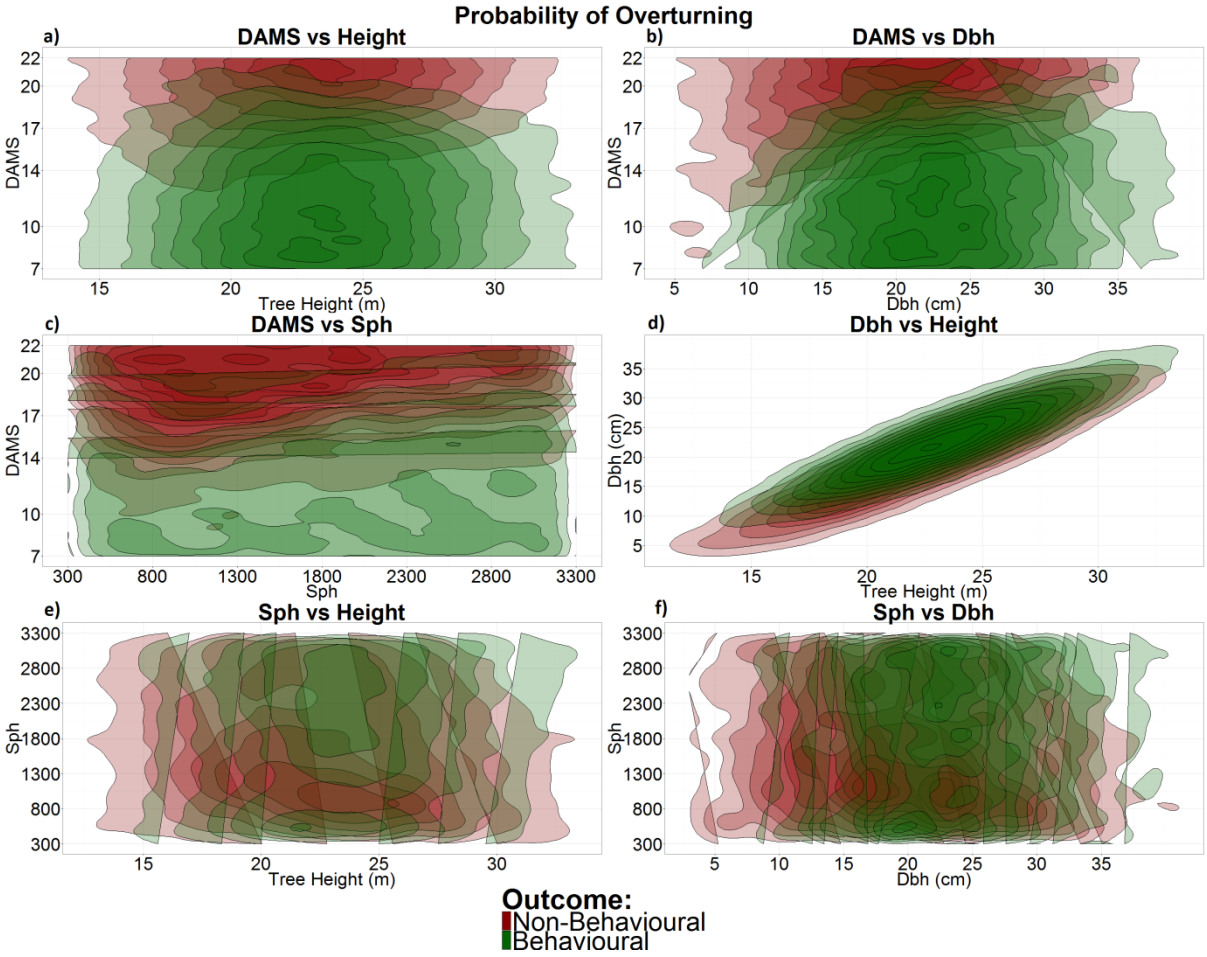

Figure 17: 2D – density plots for probability of overturning for *E. globulus*. DAMS: Detailed Aspect Method of Scoring, a measure of the windiness of a site; Dbh: diameter at breast height; Sph: stems per hectare. The green areas represent the "Behavioural" realisations of ForestGALES that correspond to a probability of damage < 0.1. The red areas correspond to "Non-behavioural" realisations, i.e. probabilities > 0.1. The intensity of the colour corresponds to the density of the outputs: darker areas have higher densities.

For *E. globulus*, the two-way interactions between DAMS, Tree height, *dbh*, and *Sph*, are almost identical for the probabilities of breakage and overturning. For breakage, short trees are at risk of failing for DAMS as low as 8 (Figure 16*a*), while for overturning *E. globulus* trees are at low risk regardless of their height, for DAMS lower than 14 (Figure 17*a*). Similarly, trees with a small *dbh* (< 10cm) are at risk of both breakage and overturning, while as *dbh* increases the windiness required to damage a tree increases linearly, with trees of *dbh* > 30cm being at risk of damage only for DAMS > 15 (figures 16*b* and 17*b*). For the interaction between DAMS and *Sph*, stands of low stocking densities are more prone to damage. However, especially for breakage (Figure 16*c*), ForestGALES predicts that low values of DAMS (between 10 and 14) can result in damage to a stand regardless of its stocking density. The *dbh* vs Tree height plots in Figures 16*d* and 17*d* show that for *E. globulus* ForestGALES cannot discriminate between high and low risk solely on the basis of these two variables, as the density areas overlap almost entirely. However, short trees with small *dbh* are predicted to be at higher risk of damage. The last two plots (*e* and *f*) in Figures 16 and 17 show that short trees, and trees with small *dbh*, are at higher risk of damage regardless of the stocking density.

Tall trees (>30m) and trees with large *dbh* (>30cm) are at lower risk when associated with high stocking densities.

4. Discussion

In this study we have performed a variance-based sensitivity analysis (SA) on the forest wind-risk model ForestGALES (Hale et al., 2015). We have used the method of Kucherenko et al. (2012), a generalisation of the Sobol' method (Sobol', 2001) for the case of correlated variables. To provide wide silvicultural and geographical applicability of our results, we have performed our analysis on the performance of ForestGALES for three tree species, representative of three of the most extensively planted and highly productive tree genera in the world: spruces (*P. sitchensis*), pines (*P. pinaster*), and eucalypts (*E. globulus*). We have focussed our sensitivity analysis only on the model input variables that are modifiable by the end-users in order to contextualise our results for practical applications of the model, as well as for the forest wind-risk modelling community. A number of settings are available when performing variance-based SA. These settings make use of different results of the SA, and provide information on different processes within the architecture of a model. In this study we have focussed on three SA settings: Factor Prioritisation (FP), Factor Fixing (FF), and Factor Mapping (FM). ForestGALES provides two pairs of outputs: the critical wind speeds for breakage and overturning ($CWS_{(B,O)}$), and the associated probabilities of damage ($Prob_{(B,O)}$). In this section we first discuss the FP and FF settings that were applied to the $CWS_{(B,O)}$, which we complement with a discussion of the similarities between species in the ranking of the most influential input variables, as identified with the FF setting. We then follow with a discussion of the results of the FM setting which was applied to the $Prob_{(B,O)}$. We conclude this section with an evaluation of the performance of the Sobol' method for correlated variables applied to our study.

4.1 Critical wind speeds – Factor Prioritisation setting

The aim of the FP setting is to identify the variables with the highest first-order sensitivity indices (S_i), not taking into account any interactions in the model between the variables. The identification of the variables with the highest S_i values allows optimising the resources required for the acquisition of accurate data for model execution. In fact, high S_i values highlight the variables that, if the uncertainty associated with their measurement or collection is reduced the most, will cause the largest reduction in the uncertainty of the outputs. The two most important variables identified by our SA are Tree height and *Sph*, regardless of tree species. For *P. sitchensis* differences exist in the ranking of these variables between CWS_B and CWS_O, with *Sph* being largely more important for the latter than Tree height. Gardiner et al. (1997) have shown that low *Sph* results in increased wind loading on a tree, promoting overturning over breakage as type of damage. For *P. sitchensis* and particularly for *E. globulus*, *dbh* is also influential. For *P. pinaster*, *dbh* is completely uninfluential, while variation in Rooting depth contributes marginally to the variation in CWS_O.

Recent advancements in the field of remote sensing can help with fast and cost-effective forest mensuration (McInerney et al., 2011; Rosette et al., 2011). For large applications of the model (i.e. in the Capsis software platform used in France, Dufour-Kowalski et al., 2012), knowledge of species

941 geographical distributions within the area of interest is recommended. However, in the case of
942 mixed-species stands the similarities between the species most influential variables provide some
943 confidence that an average level of measurement accuracy across the variables would ensure that
944 estimates of $CWS_{(B,O)}$ for large-scale investigations of vulnerability are reliable.

945 The species differences in the FP setting results pose some questions on the inner workings of
946 ForestGALES for different species. For *P. sitchensis*, the influence of Tree height is larger than that of
947 *dbh* for CWS_B, while the opposite is true for CWS_O. This is surprising since, as seen in Eq. (1) and (2),
948 dbh^3 is involved in the calculation of CWS_B, while CWS_O is calculated with stem weight, of which Tree
949 height * dbh^2 is a good approximation, as shown by Gardiner et al. (1997). However, as shown in
950 Table 2 Tree height is involved in a large number of components of CWS_B, and actually one more
951 than for CWS_O. The FP setting result of *dbh* being uninfluential for *P. pinaster* is also surprising. We
952 ascribe this to the fact that the variance of our sample data for *dbh* was the smallest of the three
953 species (see Table 3). Conversely, the variance of *dbh* was largest for *E. globulus*, and its S_i for both
954 CWS is the largest for this species. With regards to *E. globulus*, it is interesting to note that our SA
955 identified some contribution of Gap size to the variance of $CWS_{(B,O)}$, while for the other two species
956 this variable was completely uninfluential. We ascribe this to the fact that in our *E. globulus* sample
957 there is no variation of Rooting depth and Soil type, which therefore cannot outweigh the influence
958 of Gap size, as it is likely to be the case for the other two species. While it is true that Rooting
959 depth's S_i for *E. globulus* is quite high (0.10, Figure 5), its S^T_i is zero. Given that there is no variation in
960 Rooting depth and Soil type for *E. globulus*, the non-zero S_i value of Rooting depth is necessarily a
961 mistake in the numerical estimation of the sensitivity indices. Rooting depth is more influential for *P.*
962 *pinaster* than for *P. sitchensis* (S_i values of 0.13 and 0.01 for CWS_O, Figures 4 and 3, respectively). The
963 likely reason for this is the larger variation in the C_{reg} values for *P. pinaster* than for *P. sitchensis*
964 (Table 1). While *P. pinaster*'s C_{reg} values for three soil types (Gleys, Mineral peats, and Deep peats)
965 are actually taken from tree-pulling on *P. sylvestris* (in Nicoll et al., 2006), the largest variation can be
966 seen in the *P. pinaster* bespoke tree-pulling experiments (Cucchi et al., 2004).

967

968 *4.2 Critical wind speeds – Factor Fixing setting*

969 The FF setting is based on the total sensitivity indices (S^T_i) and provides information on the
970 interactions within the model between variables, and on which variables can be confidently fixed at
971 any value within their range without significantly affecting the predictive potential of the model. We
972 first discuss the interactions in ForestGALES, before discussing the issue with fixing variables.

973 A large difference between a variable's S_i and S^T_i indicate that the variable is involved in a large
974 number of interactions. As expected from Eq. (1) and (2) and Table 2, the largest interactions are
975 expected to be found between Tree height and *dbh*, with *Sph* contributing in a much smaller
976 measure. In fact, our results show that the other variables are not involved in significant
977 interactions, as their S^T_i are basically zero. The largest interactions between Tree height and *dbh* are
978 found for *P. pinaster*, with *Sph* marginally involved (Figure 4). Based on the Sobol' indices in Figure 3,
979 for *P. sitchensis* the interactions between Tree height and *dbh* are of similar magnitude to those of *P.*
980 *pinaster*, while *Sph* is not involved in interactions, with CWS_B showing larger interactions than CWS_O.
981 For *E. globulus*, the interactions between Tree height and *dbh* are much smaller than for the other
982 species, while those with *Sph* are of similar magnitude to *P. pinaster*.

Besides the estimation of interactions between variables, the most significant outcome of applying the FF setting is to identify the variables that contribute negligibly to the variance of the output. This has practical advantages, in that when data collection is costly or impractical, resources can be displaced from sampling variables with low S^T_i to those that show a large influence on the output. In the case of ForestGALES, our results calculated negligible S^T_i for Rooting depth, Soil type, and Gap size. The first two are related in ForestGALES as they are used to retrieve the C_{reg} values used in the calculation of CWS_O (Eq. 2), and as such are discussed together. Our results suggest that accurate knowledge of Rooting depth and Soil type is not necessary, and that only minor approximation errors would follow from fixing these variables to any value within their ranges. These findings suggest that, when Rooting depth and Soil type are not known and would be expensive/impractical to investigate (as for owners and managers of small forested stands), or when they are very heterogeneous (as in the case of large-scale studies of wind damage), these variables can be quite confidently ignored. In fact, the approximation errors shown in Table 5 for fixing Rooting depth or Soil type are never larger than 6%. For *P. sitchensis* and *P. pinaster*, when we fixed these variables to the values within their ranges, we did notice some small differences with the "Free" simulations where all the variables were allowed to vary at the same time. There is no variation in the C_{reg} values for *E. globulus* (Locatelli et al., 2016), which is therefore not discussed here. We ascribe the relatively high S_i value of Rooting depth for *E. globulus* (0.10) to a numerical imprecision in the calculations. Indeed, the same value is found for CWS_B, and the associated S^T_i were zero. For *P. sitchensis*, fixing Rooting depth to deep rooting resulted in an overestimation of CWS_O, showing more resistance to overturning (Figure 8). Similarly, overestimation of CWS_O was found when we fixed Soil type to "Freely draining" and "Deep peats", as the average C_{reg} values shown in Table 1 for these soil types are the largest for *P. sitchensis.* Conversely, underestimation of CWS_O was found when Soil type was fixed at "Gleys" and "Mineral Peats". For *P. pinaster*, fixing Rooting depth to medium resulted in overestimating CWS_O (Figure 9), as did fixing Soil type to "Deep peats". Underestimation of CWS_O was found when Soil type was fixed at "Gleys". These results are consistent with the C_{reg} values shown in Table 1 for combinations of Rooting depth and Soil type. However, as seen in Figures 8 and 9, these over- and underestimations are relatively minor and mostly affect simulated trees associated with very large CWS_O, suggesting that the contribution of Rooting depth and Soil type to the calculations of ForestGALES is mostly relevant in cases of catastrophic wind speeds, i.e. when forest management practices are of minor importance (Kohnle et al., 2003). This reinforces our conclusion that Rooting depth and Soil type are of minor importance to the use of ForestGALES.

With regards to the influence of Gap size on $CWS_{(B,O)}$, the Sobol' indices in Figures 3, 4, and 5, suggest that while for *P. sitchensis* and *P. pinaster* Gap size has no influence, it does have an effect on *E. globulus*. However, the scatterplots in Figures 6 and 7 show that fixing Gap size had an effect on the calculations of the critical wind speeds for all three species. This is especially evident for Gap size = 0m, which resulted in large overestimations, especially for *E. globulus*. Fixing Gap size to the other values (1000m and 10 times Tree height) resulted in underestimation of $CWS_{(B,O)}$, especially for wind speeds over 25 m s^{-1}, but never for very high $CWS_{(B,O)}$. The effect is more evident for *E. globulus*. Gap size fixed at 2 times Tree height caused minor overestimation of $CWS_{(B,O)}$ for *P. sitchensis* and *P. pinaster*, also for low wind speeds. For *E. globulus*, the effect is complex, with over and underestimation of the CWS. This is particularly marked for overturning, where very low CWS are affected by the change. Fixing Gap size at 0m means that the stand is part of a continuous forest. As shown by Gardiner et al. (1997), this has the effect of modifying the wind profile, resulting in less

loading on the trees (i.e. higher CWS are required to damage a tree within a forest continuum). Our results confirm this, showing that ForestGALES is able to simulate the effect of Gap size even in the case of green edges. In their study on the risk of wind damage to three conifer species, Mitchell et al. (2001) have shown that the likelihood of damage increased with creation of new edges, and persisted for a period of time insufficient for the newly exposed trees to acclimate to the new wind loading at the edges. Their findings on the effect of newly created edges were confirmed by Scott and Mitchell (2005) in their study on the effect of large upwind gaps. In their simulation study on the susceptibility of stands composed of two conifer species to wind damage in Finland, Zeng et al. (2010) concluded that the presence of upwind gaps increases the risk of wind damage to a stand more than its species composition. A number of simulation studies centred on the use of complex airflow models (either based on Large – Eddy Simulation techniques, or high – resolution Reynolds – averaged type models) have shed some light on some of the possible reasons for the effect of gap creation on the risk of wind damage. Dupont et al. (2015a, 2015b) have shown that as gaps are formed, more gusts penetrate the forest canopy, increasing the wind loading on trees. As shown in Figures 6 and 7, the effect of fixing Gap size to 0m is evident also at very high CWS, while fixing it to the other values only results in underestimation for medium to moderately high CWS. As the results of the Savage scores indicate (Table 6), Tree height, *dbh*, and *Sph* are the most influential variables in driving the CWS, regardless of tree species. Therefore, high CWS must be associated with short trees, large *dbh*, and mid-to-high values of *Sph* (the latter is shown in the discussion of the probabilities of damage). This is confirmed with data shown in the Appendix: when we isolated the simulated trees associated with extreme CWS (over 75 m s^{-1} for *P. sitchensis*; over 50 m s^{-1} for *P. pinaster*; over 35 m s^{-1} for *E. globulus*), we noticed that these trees were mostly short and their *dbh* was large (trees had a large taper), and stocking densities were medium to high. Therefore, for Gap size to be able to have such a large effect when fixed at 0m, it must be more important than estimated with the indices of Sobol'. The Sobol' indices were however able to identify Gap size as more important for *E. globulus* than for the other two species, which is confirmed by our investigation of tree characteristics for extreme CWS shown in the Appendix. In fact, there is much more variation in Tree height, *dbh*, and *Sph* for *E. globulus* trees than for the other species. That is, these trees are taller, their *dbh* is not necessarily large, and stocking densities are as low as ~300 *Sph*. Considering that our simulated *E. globulus* trees are much slender than those of the other two species, and are therefore at higher risk of wind damage, the larger effect of fixing Gap size to 0m is to be expected. Locatelli et al. (2016) performed a GSA with the method of Kucherenko et al. (2012) on their parameterisation of ForestGALES for *E. globulus*. Their results show that, when Gap was allowed to vary within the same range as in our study, its influence on the CWS was significant, and the interactions between Tree height, *dbh*, *Sph*, and Gap size were very large. The authors used a version of ForestGALES where upwind gaps were brown edges, i.e. gaps recently formed. This suggests that variation of Gap size for newly created gaps has a larger influence on the dynamics of ForestGALES than when the gaps are of the green edge type.

The FF setting can also highlight inadequacies in the modelling of processes that include variables that are found to be important in the natural world. In our study, this is likely to be the case of the influence of Rooting depth and Soil type on overturning. A number of surveys of wind damaged stands have provided information on the factors associated with wind damage to forests. Although these studies often do not discriminate between breakage and uprooting, they suggest that variation in soil type and rooting depth are important drivers of wind damage (e.g. Hanewinkel et al.,

2008; Mayer et al., 2005; Nilsson et al., 2004; Schindler et al., 2009). The authors report that shallow rooting, waterlogged soils, and acidic soils, increase the risk of wind damage. These stand characteristics are often time-consuming, expensive, and difficult to measure both during tree-pulling experiments and in forest inventories. These constraints, together with the current scarcity of easily implementable, fully mechanistic methods of modelling tree anchorage, have forced wind damage modellers to adopt an empirical approach to model trees' resistance to uprooting that is limited to easily obtainable characteristics of the root and soil system, such as coarse classifications of soil type and rooting depth. Examples of the complexities of the effect of soil conditions on the risk of uprooting can be found, e.g. in Ray and Nicoll (1998), and more recently in Kamimura et al. (2012). In their investigation of the effect of waterlogging soils prior to tree-pulling experiments, Kamimura et al. (2012) identified that soil water content influenced tree anchorage in a complex fashion, highly dependent on whether water was concentrated within the soil-root plate, or below it. Heavier, water-saturated root plates provided the trees with initial higher stability, while large water content below the plates can lead to hydraulic fracturing in the soil.

4.3 Difference between species

As shown by Iman and Conover (1987), the calculation of the top-down coefficient of concordance amongst all species (C_T) is strongly driven by agreement between the top ranks. This can be seen in the calculation of the Savage scores with Eq. (6). The importance of at least a degree of accordance between the top three ranks in driving the calculation of the T_{all} index is further corroborated by the numerator of Eq. (7): the more similar the top ranks are amongst species, and the larger the number of species, the larger C_T (and therefore T_{all}) becomes. As a result, the probability of the T_{all} index to be larger than the upper-tail critical value of a chi-square distribution (in our case, with 5 degrees of freedom) diminishes as C_T and T_{all} increase.

With regards to the pairwise comparisons between our species, certain differences are evident. For CWS_B, the ranking of the S^T_i of *E. globulus* is markedly different from the other two (Figures 3, 4, and 5). This is reflected by the *p*-values in Table 6 for the comparisons that include *E. globulus* being the largest (0.247), while the *p*-value of the comparison between *P. sitchensis* and *P. pinaster* (0.087) indicates that differences between these two species are almost non-significant at the 95% confidence interval. It should be noted that the fact that the S^T_i rankings of these two species are identical (Figures 3 and 4) suggests that the accuracy of our statistical test is not perfect. For CWS_B, the large *p*-values (0.237 and 0.246) for the comparisons between *P. sitchensis* / *E. globulus*, and *P. pinaster* / *E. globulus*, are driven by the fact that the ranking of the top two variables, Tree height and *dbh*, are inverted between the pair (*P. sitchensis*, *P. pinaster*), and *E. globulus*. In fact, the difference between the Savage scores calculated for the top rank, and the second or the third rank, are quite significant (top rank: 2.45; second rank: 1.45; third rank: 0.95), while further ranks, especially in the case of ties (e.g. for Rooting Depth and Soil type) have similar low values, below 0.5. Therefore, in pairwise comparisons a small disagreement at the top three ranks can result in the S^T_i rankings of the 2 species being flagged as substantially different. This is unlike in the calculations of C_T and T_{all}, for which partial agreements between the top S^T_i rankings of the three species contributes to the degree of similarity between all three species. Similarly, the small, but non-zero S^T_i of Gap for *E. globulus* contributes marginally to these pairwise differences that involve *E. globulus*,

as its rank is higher than for the other two species. For CWS_O, the difference between *P. sitchensis* and *P. pinaster* (*p*-value 0.448) is due to the different ranks of the top three variables (Tree height, *dbh*, and *Sph*). For the *P. pinaster* / *E. globulus* pair, the large *p*-value (0.273) is due to the rankings of Tree height, *dbh*, and Gap size. Similarly, the difference between *P. sitchensis* and *E. globulus* (*p*-value 0.128) is attributable to the rankings of Tree height, *Sph*, and Gap size.

4.4 Probabilities of damage – Factor Mapping setting

The FM setting is a form of Monte Carlo filtering, in that it divides the output space in acceptable and unacceptable regions, and maps the realisations of the model in these regions back to the input space. We have applied this setting to the probabilities of breakage and overturning, and we have chosen the probability threshold to differentiate between the two regions in the output space as 0.1 (10% probability of damage). Our results show that DAMS, the variable that describes the intensity of the wind, is the most responsible for realisation of $Prob_{(B,O)}$ in the two regions of the output space, regardless of tree species. DAMS values range from 7 to 22, with 20 often regarded as the limit for commercial forestry (Quine, 2000). Our SA shows that DAMS values over ~15 are much more likely to result in damage to a stand, regardless of the mode of failure (breakage or overturning) and tree species. This finding suggests that ForestGALES describes well the effect of the wind climate on the probabilities of damage. In fact, it is well known that in the case of extreme wind storm, the effect of silvicultural practices on tree survival is minor (Kohnle et al., 2003), while for sheltered stands the effect of stand and tree characteristics is more prominent (Albrecht et al., 2012). This raises the issue of the availability of accurate wind speed data, which can be obtained only from localised climate stations. While methods to extrapolate spatially the wind speeds exist (e.g. the Wind Atlas Analysis and Application Program (WAsP) used for estimates of wind energy productivity), their extrapolations are not devoid of error, especially in the case of complex terrain or large distances from the data source (Venäläinen et al., 2004). Mayer et al. (2005) have shown that when knowledge of wind speeds during a storm is accurate, wind speeds become important in statistical models used to discriminate between areas with and without wind damage.

The results of the FM setting show some similarities between *P. sitchensis* and *P. pinaster*, and therefore these two species are discussed together. *E. globulus* behaved quite differently, probably due to the tall trees with low taper used in our simulations, and is discussed separately. The results of the Smirnov tests generally agree with the Sobol' S_i calculated for $CWS_{(B,O)}$ for all the species. For *P. pinaster*, this means that *dbh* was found to be uninfluential with the Smirnov tests. The role of *dbh* in driving the outputs is important for *P. sitchensis*. Our results (Figures 11 and Table 7) show that the risk of breakage and overturning decreases for trees with a *dbh* larger than 10cm. Both conifer species respond similarly with regards to *Sph*, as intermediate values (~1500 sph) correspond to lower risk. No threshold could be identified for Tree height. For $Prob_O$, DAMS values lower than 10 did not cause any damage to the simulated stands of the two species (Table 7). The results of our bivariate investigations of the relationship between significant variables with regards to $Prob_{(B,O)}$ show some differences between the two species. For *P. sitchensis*, the two modes of damage show similarities (Figures 12 and 13). The DAMS vs Tree height density plots show that short trees (Tree height < 10m) are at lower risk of damage regardless of the wind speed, and that no damage was estimated below DAMS ~ 13. We ascribe this behaviour to the form of the *P. sitchensis* trees in our

simulations, which are characterised by high taper (Table 3). For breakage, *P. pinaster* behaves very similarly, while for overturning higher wind speeds are required for damage (DAMS > 16, Figure 15). For both species and both $Prob_{(B,O)}$, the DAMS vs *dbh* plots show a diminished importance of wind speed when trees have large *dbh*. The role of taper in driving the probabilities of damage is evident from the *dbh* vs Tree height density plots. The separation between the clouds of points is quite clear, showing that trees of the same height are at lower risk of damage when their *dbh* is large. This finding confirms that ForestGALES simulates effectively the well-known effect of taper on the risk of wind damage (e.g. Peltola and Kellomaki, 1993; Quine et al., 1995). For *P. pinaster*, only trees taller than ~10.5m were considered at risk of damage. The role of *Sph* is the same for both species and both modes of damage. The DAMS vs *Sph* plots show that at low stocking densities the probabilities of damage are higher than 10% for DAMS as low as 12, while at high stocking densities damage is predicted only at high DAMS. The relationship between *Sph* and Tree height in ForestGALES is such that short trees in sparse stands are at lower risk of damage, while trees above 11m are associated with damage regardless of stocking density. Conversely, trees of medium to large *dbh* are mostly at risk for low *Sph*, while low *dbh* is associated with damage regardless of the stocking density, but mostly at low *Sph*. The effect of dense stands is quite constant for the two species, with large stocking densities being associated with lower risk of damage. With regards to *Sph*, ForestGALES behaves in accordance with the findings of Coutts (1986), who reported less damage in dense *P. sitchensis* stands. Gardiner et al. (1997) showed that low stocking densities result in higher wind loading on the trees, despite the gustiness of the wind decreases with decreasing *Sph*. The authors showed that the maximum bending moment increases faster than the Gust Factor decreases, as stocking densities decrease.

The FM results for *E. globulus* differ partially from those of the other two species. For both types of damage, the *Sph* thresholds are lower (~ 1000 sph), as are the associated D-statistic values (Table 7), suggesting that for *E. globulus Sph* is less important in discriminating between high and low probabilities of damage. The density plots (Figures 16 and 17) show that our simulated *E. globulus* trees are at higher risk of damage than the other species, and that DAMS is much more important than *Sph*, which is in turn much more important than Tree height and *dbh* in discriminating between damage and no damage. The DAMS vs Tree height and *dbh* plots are very similar, showing that small trees are vulnerable to damage even at low wind speeds (DAMS ~8) while larger trees require DAMS to exceed 14 for the probabilities of damage to exceed 10%. This trend is confirmed by the Tree height vs *dbh* plot. We ascribe the similarities between the response of Tree height and *dbh*, and the relatively low importance of *Sph*, to the high taper of our *E. globulus* trees, which probably largely influenced the calculations of $Prob_{(B,O)}$, as it did for $CWS_{(B,O)}$.

4.5 Evaluation of the performance of our GSA

The most important step of variance-based methods of sensitivity analysis is the characterisation of the variables with reliable probability distribution functions. In order to investigate the behaviour and sensitivity of the ForestGALES model, in our study we have adopted a data-driven approach, as we fitted PDFs to Tree height and *dbh* from available tree-pulling data, to ensure that the model is investigated within the limits of its parameterisations for different species. Large trees are typically under-represented in these field experiments for safety reasons and technical limitations (Nicoll et

al., 2006), even more so for data that was gathered in the past (Fraser and Gardiner, 1967). As a consequence, tall trees are under-represented in the *P. sitchensis* and *P. pinaster* tree-pulling datasets that were used for the PDFs in our study, while short trees with a high taper are common. The high correlation coefficient between Tree height and *dbh* (*P. sitchensis*: 0.54; *P. pinaster*: 0.73; *p*-values < 0.001) resulted in our simulated trees for the two conifer species to be quite short and with a high taper. The stability of high tapering trees with regards to wind damage is well known, especially for breakage (e.g. Slodicak and Novak, 2006; Valinger and Lundqvist, 1992). As shown by Zubizarreta-Gerendiain et al. (2012), regardless of species trees with a high taper are associated with lower risk of uprooting, a tenet which is often interpreted as trees with larger diameters in the lower stem having likely allocated more resources in the formation of extensive root systems (Nicoll and Ray, 1996). This is reflected in our ForestGALES simulations, with low-tapered *P. sitchensis* and *P. pinaster* trees being at lower risk of uprooting (i.e. higher CWS_O) than the more slender *E. globulus* (Figures 8, 9, and 10).

In addition to this, the taper of our simulated trees was independent of the stocking density, which is not representative of reality. As discussed in the previous paragraphs, these factors have a significant impact on the ForestGALES calculations of the critical wind speeds and their associated probabilities of damage. Consequently, the influence of *Sph* on the outputs of ForestGALES was probably underestimated in our GSA, as shown by the small differences between total and first-order sensitivity indices for *Sph*. This is likely to be the case also for *E. globulus*, for a similar but opposite reason. In fact, our simulated eucalypt trees are fairly tall and slender, with a very high taper. Because of the importance of Tree height, *dbh*, and taper in ForestGALES, the outputs are likely to have been mostly driven by Tree height and *dbh*, while the role of *Sph* was probably outweighed. The effect of this can be seen in the smaller range of $CWS_{(B,O)}$ for *E. globulus* in comparison to the other species, as seen in Figures 6 and 7. Although Tree height and *dbh*, and their high correlation (0.91, *p*-value < 0.001) are representative of the fieldwork data used to calculate the parameters of the corresponding PDFs, the source of our *E. globulus* data has some limitations and might not be representative of all eucalypt stands (Locatelli et al., 2016). Nevertheless, our GSA allowed us to highlight the limitations of the parameterisation of ForestGALES for this species. Our study shows that the GSA method of Kucherenko et al. (2012) is very sensitive to the correlations between variables in the correlation matrix of the copula. Therefore, it requires an accurate characterisation not only of the PDFs of the inputs, but also of their initial correlation matrix. This is important, to ensure that the generated dataset used for the SA is representative of the original sample's structure.

We described Rooting depth and Soil type with uniform discrete distributions in order to explore the input space more thoroughly, but we did impose a correlation based on *P. sitchensis* data. This might not be representative of *P. pinaster*, and might have marginally influenced our results for this species. Gap size is the variable that is most likely to have been poorly characterised using the range of values in our simulations. As shown in Figures 6 and 7, fixing Gap size to 0m has a large effect on the calculations of the CWS; at just two tree heights, however, the effect is largely diminished, while fixing Gap size at values as low as 10 times Tree height has an almost negligible effect. However, the model runs where Gap had values close to 0m were not sufficient to influence the calculations of the Sobol' indices. A Gap of the size of twice the mean Tree heights shown in Table 3 belongs to the first quartile of the range of Gap size. Therefore, most of our simulations had values that exceed this

average value, and this likely influenced the calculations of the Sobol' indices. We expect that a narrower range of Gap size would have resulted in larger Sobol' indices for this variable.

5. Conclusion

In this study we have performed a variance-based sensitivity analysis on the forest wind-risk model ForestGALES, for three species (*P. sitchensis*, *P. pinaster*, and *E. globulus*) representative of three of the most extensively planted and highly productive tree genera worldwide: spruces, pines, and eucalypts. The application of the variance-based sensitivity analysis method for correlated variables shows great sensitivity not only to the characterisation of the variables with appropriate probability density functions, but also to the correlation matrix of the variables. Therefore, particular care must be exercised when describing the input data for this method of sensitivity analysis. Our results show that Tree height, *dbh*, and stocking density are the tree and stand variables mostly responsible for the variation in the critical wind speeds for breakage and overturning, regardless of tree species, although minor intraspecific differences exist in the ranking of these variables. These variables, together with the wind climate local to a stand, as expressed by the DAMS variable, are the major drivers of variation in the associated probabilities of damage. Therefore, for practical applications of ForestGALES, users should focus their resources on sampling accurately these three tree and stand variables to maximally reduce the uncertainty in the predictions of the model. Our study shows that Rooting depth and Soil type are only marginally important for the calculations of the critical wind speed of overturning. This finding suggests that these variables can be fixed at any value within their ranges without significantly affecting the output of the model, thus suggesting that ForestGALES can be successfully applied to large-scale studies of wind damage when information on these variables is coarse at best. While there is not a general consensus on the role of rooting depth and soil type on the vulnerability of a stand to wind damage, our study suggests that the empirical component of ForestGALES that calculates the resistance to overturning requires further development. The effect of an upwind gap on the critical wind speeds is confirmed also for pre-existing forest edges, suggesting that recommendations made with ForestGALES on the careful management of forest edges to reduce the risk of damage are to be considered seriously, namely avoiding Gap sizes larger than twice the mean height of the stand.

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